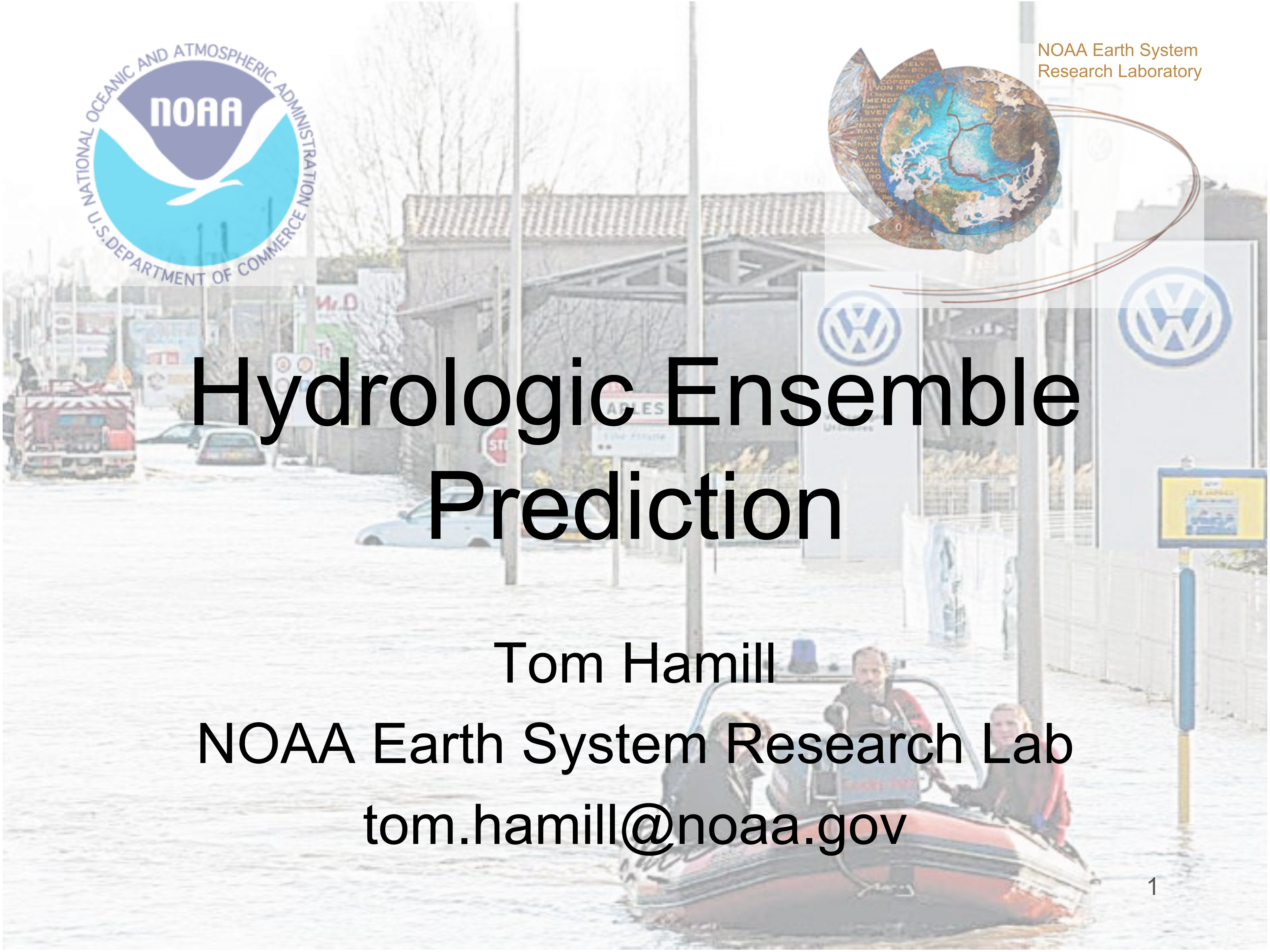

NOAA Earth System
Research Laboratory

Hydrologic Ensemble Prediction

Tom Hamill
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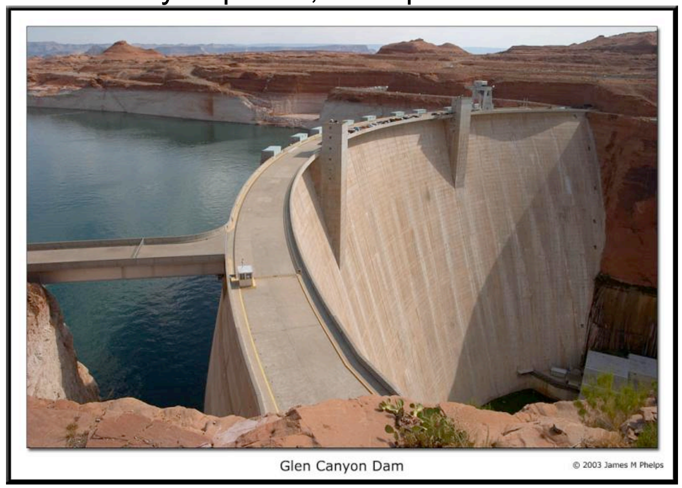
Some motivations for hydrologic prediction

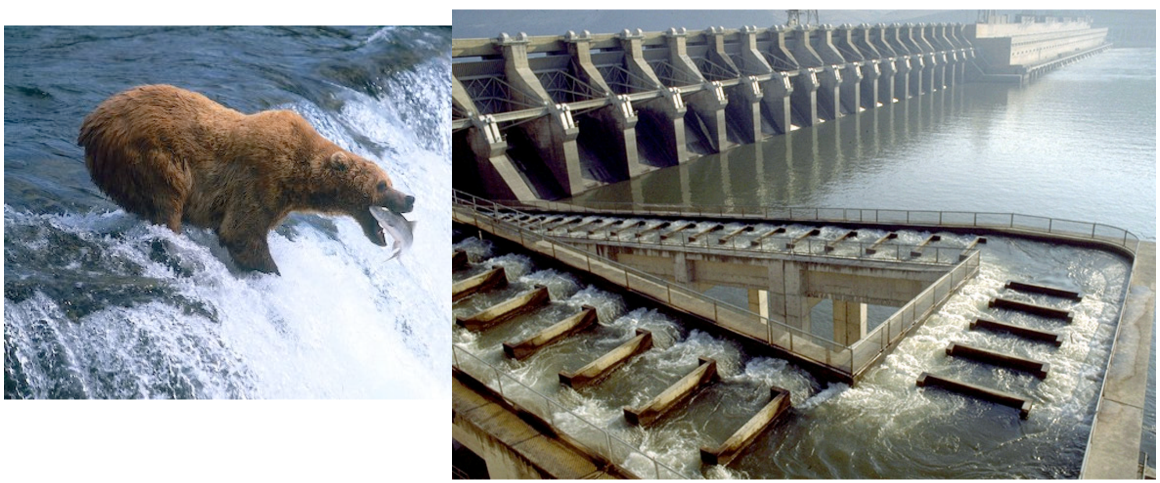
Flood forecasting

Hydropower, flood protection



Irrigation

Managing natural resources



Recreation

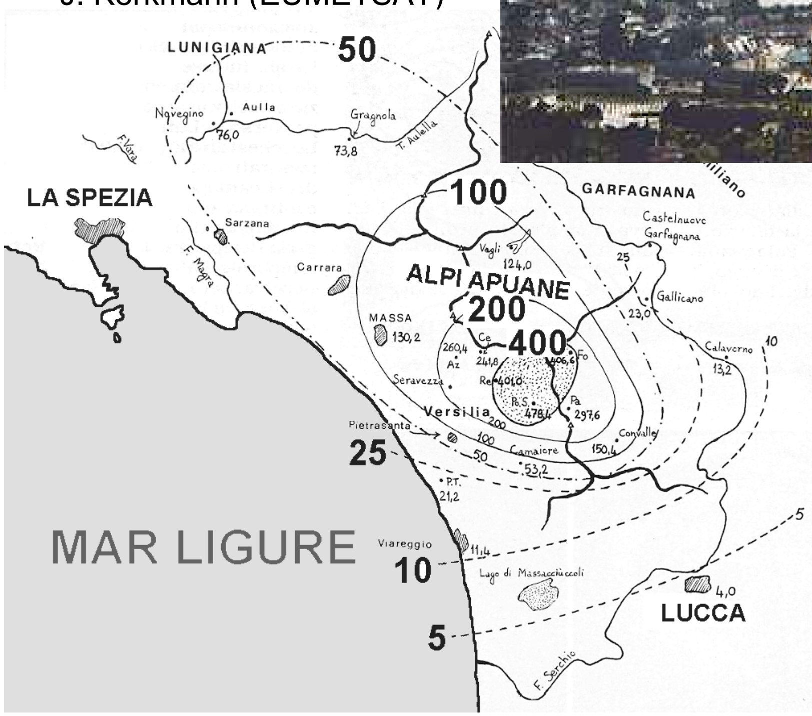
Topics

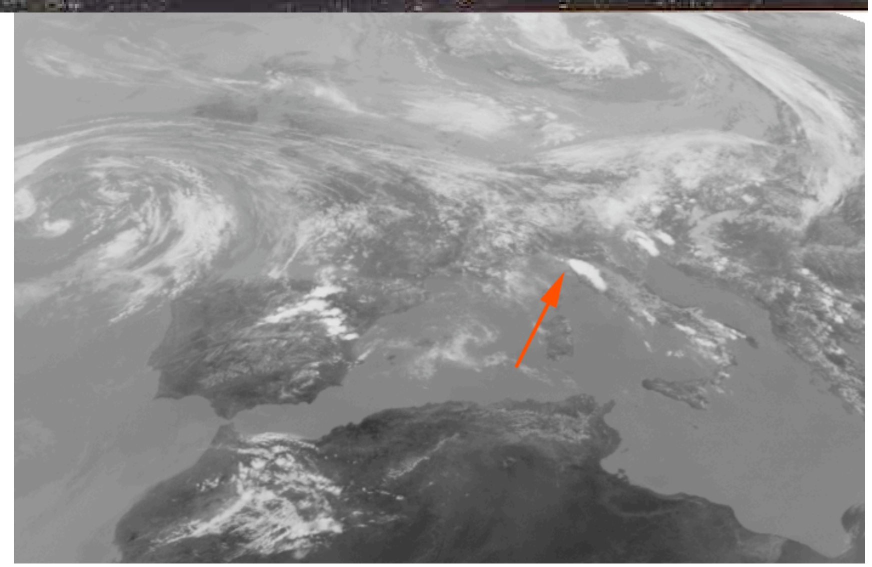
- Sources of hydrologic forecast skill
- Past and present hydrologic prediction systems.
- Future ensemble hydrologic prediction systems and technological challenges
  - coupling with weather-climate ensembles.
  - data and hydrologic data assimilation issues.
  - hydrologic ensemble modeling issues.
  - verification issues.

Sources of hydrologic forecast skill for very small basins, very short leads

- Good weather forecast/nowcast/observations; satellite, radar observations crucial for improving flash-flood predictions.
- Especially dry, moist, rain-on-snow, or fire-baked soils can exacerbate flooding.

Flash flood in Versilia and Garfagnana (Apuan Alps, Tuscany, Italy) 19 June 1996
J. Kerkmann (EUMETSAT)





Hydrologic predictability, short leads

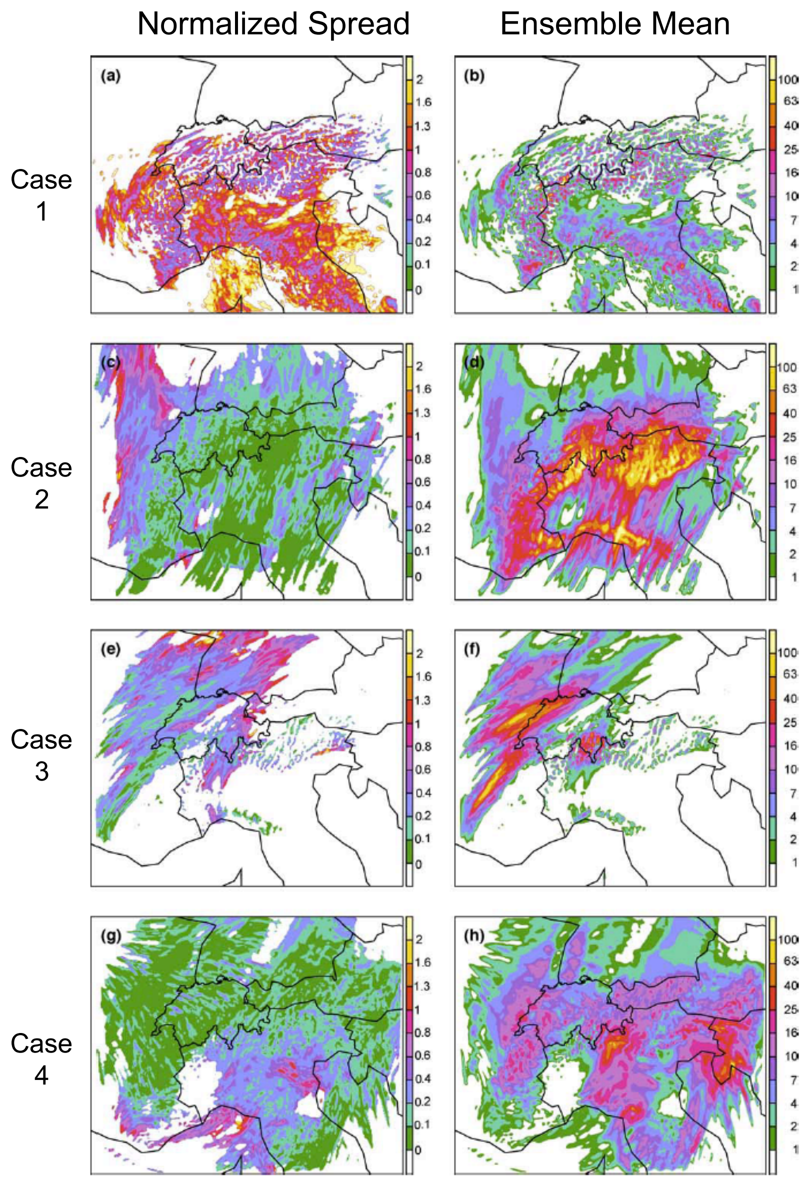


Fig. 8. Spatial distribution of (left) normalised ensemble spread S_p of accumulated daily precipitation (see text), and (right) ensemble mean of accumulated daily precipitation (mm) for (a,b) 29 Jul 1999, (c,d) 20 Sep 1999, (e,f) 25 Sep 1999, (g,h) 6 Nov 1999. The panels show the MC2 3 km model domain without the relaxation zone.

Ensemble forecasts for 4 flooding events in Italy.

$$S_p = \frac{1}{\bar{p}} \sqrt{\frac{1}{M-1} \sum_{m=1}^{M} (p_m - \bar{p})^2},$$

- Plots of forecast normalized spread and ensemble mean.
- Synoptic scale events more predictable than convective-dominated events.
- More predictability in complex terrain (not shown).

Ref: Walser and Schär, *J. Hydrology*, 2004

Example: 1-2 day lead hydrologic forecast for a basin in Northern Italy

Hydrologic model forced with multi-model weather ensemble data.

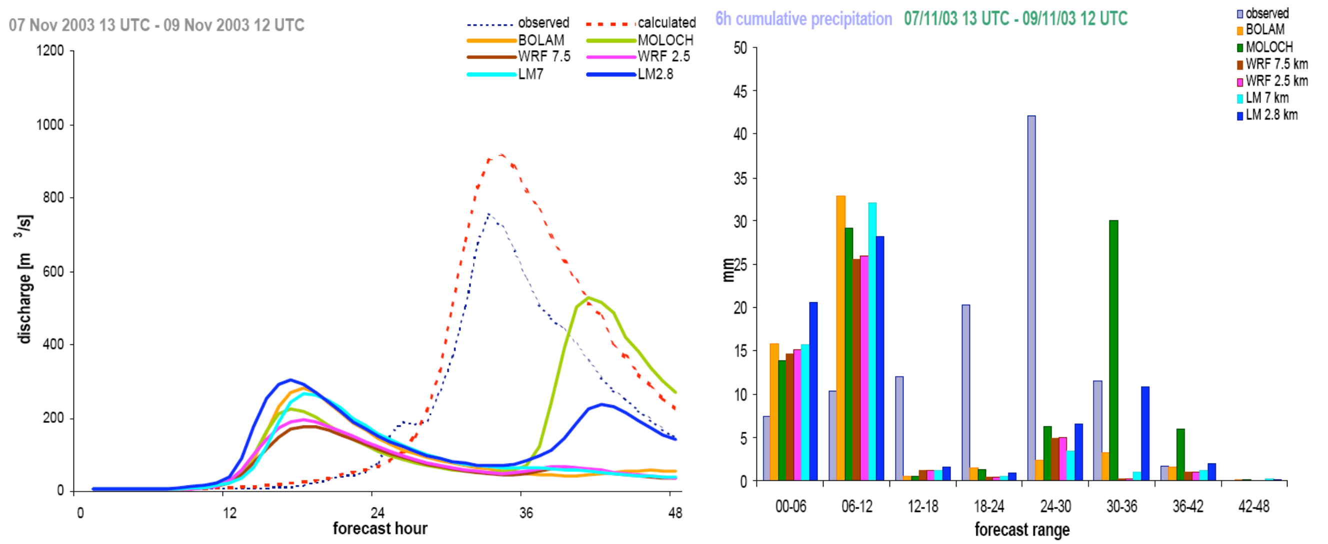


Figure 2. The 07-09 November 2003 event: streamflow forecast (left panel; m^3/s) and QPF averaged over the basin and accumulated over 6-hour periods (right panel; mm), as a function of the forecast range (hours). The different discharge curves have been obtained by feeding the TOPKAPI model with the precipitation forecast by the different meteorological models and with the raingauge observations (red dashed line). The observed discharge (blue dotted line) is also plotted for reference.

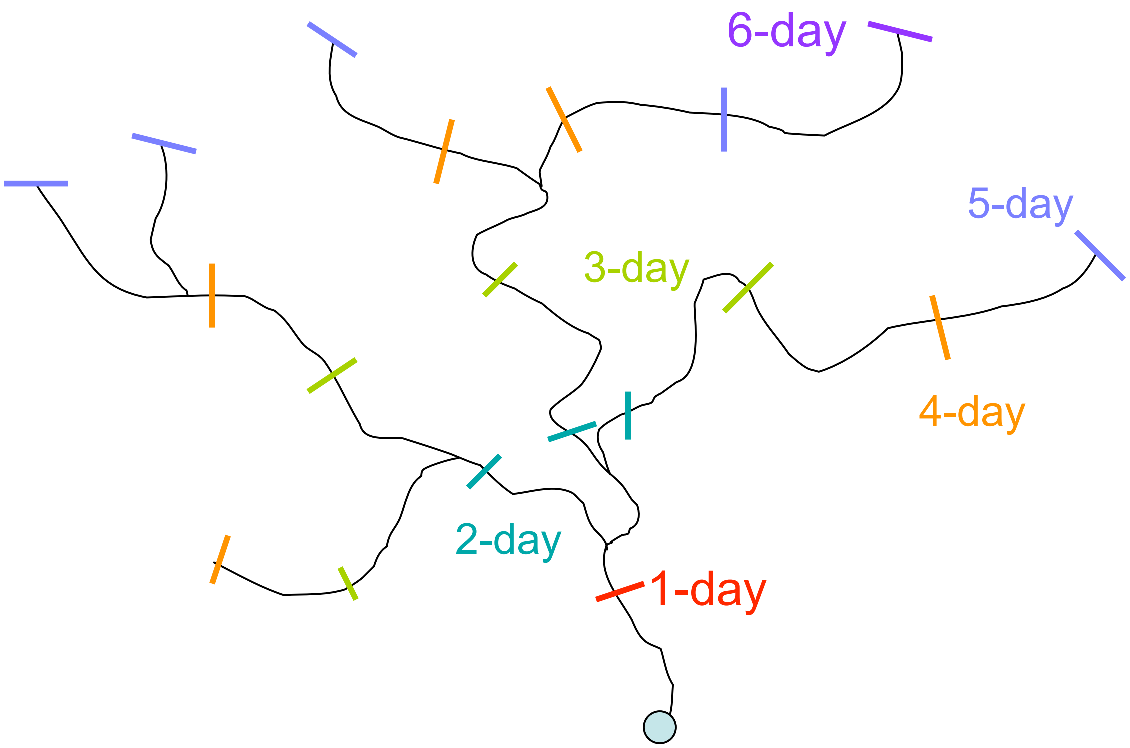
Skill of hydrologic forecast tied to the skill of the precipitation/temperature forecasts. Here, all forecasts missed timing of rainfall event, so subsequent hydrologic forecasts missed event. Reservoir regulation, hydrologic model may have also had effects.

?

Source: A meteo-hydrological prediction system based on a multi-model approach for ensemble precipitation forecasting. Tomasso Diomede et al, ARPA-SIM, Bologna, Italy.

Sources of hydrologic skill: medium basins, medium leads

- Modeling of the land state (snow, soil moisture), observed precipitation, upstream river conditions can be important.
- Weather-climate forecasts may have beneficial impact, e.g., sudden warming diminishing snowpack.



An *n*-day hydrologic forecast in this basin with its 6-day transit time requires 6-*n* days of observations and *n* days of forecasts.

(Actually, commonly even longer than 6-n days of observations to spin up and tune hydrology model)

Sources of hydrologic forecast skill: large basins, long leads

- Diminishing influence of weather and climate forecasts due to large errors at longer leads. Small signals from ENSO and such.
- Deviations from climatology largely tied to land state / snowpack.

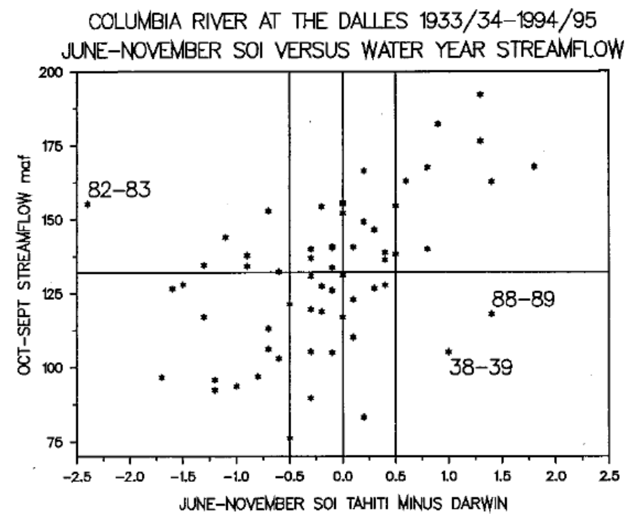


FIG. 4. June–November Tahiti – Darwin Southern Oscillation index vs subsequent October–September 12-month streamflow of the Columbia River at The Dalles, Oregon. Years 1933–34 through 1994–95. Average flow for this period is 131.47 maf. Correlation $r = 0.45$, $n = 62$ yr ($p < 0.000$). For SOI > +0.50, mean = 155.6, median = 162.7 maf, $n = 12$. For SOI < –0.50, mean = 117.99 maf, median = 119.2 maf, $n = 20$, t test of difference = 4.194 ($p < 0.0005$). Ratio of (SOI+/SOI–) = 132%.

Ref: Pulwarty and Redmond, *BAMS*, March 1997

Table 1. Summary of Climate Signals Exhibiting 95% Significant Teleconnection to the Indicated Pattern of Runoff Variability for the Designated Season and Lead Time[a]

	Lead 0	Lead 1	Lead 2	Lead 3	Lead 4
East/Mid-Atlantic/Gulf					
DJF	Nino3.4(−)	Nino3.4(−), PDO(−)	AMO(+)	AO(−), NAO(−)	
MAM	Nino3.4(+)		Nino3.4(+)		
JJA	PDO(+)			PDO(−)	
SON			AO(−)		AO(−)
Far West/Great Basin					
DJF		NP(+)			
MAM					AO(−)
JJA	AO(+)	NAO(−), NP(+), PDO(−)			Nino3.4(−), AMO(+)
SON		AO(+)	NP(−)		
Ohio/Tennessee Basin					
DJF	NP(−)			AO(−), AMO(+)	
MAM	PDO(−)	Nino3.4(−)			
JJA	PDO(±)	NP(+), PDO(−)			
SON	AMO(+)	AMO(+)	AO(+), AMO(+)		
Southern Plains					
DJF	PDO(−)	Nino3.4(−), PDO(−), AMO(−)			NAO(+)
MAM	Nino3.4(+), PDO(−)	Nino3.4(+), PDO(+)		Nino3.4(+)	
JJA	PDO(−)	AO(+)			AO(−)
SON	Nino3.4(−)				
New England/Quebec					
DJF				NP(−)	
MAM	NAO(+)			AO(−), NAO(−)	NAO(−)
JJA	NAO(−)		PDO(−)	PDO(−)	NAO(−)
SON	PDO(+)	AO(+), Nino3.4(+)	AO(+), PDO(−)	AMO(+)	
Southwest/Mexico					
DJF	NP(−)	Nino3.4(−)	PDO(−), AMO(+)	PDO(−)	PDO(−), AMO(+)
MAM	Nino3.4(±), PDO(−)	AO(+), NAO(−), Nino3.4(±)	Nino3.4(−)	Nino3.4(−), AMO(+)	AMO(+)
Upper Mississippi					
DJF	PDO(−)			NP(−)	PDO(+)
Upper Missouri/Canadian Prairie					
DJF			NAO(−)		
MAM	PDO(+)		PDO(+)	PDO(+)	AO(+)
JJA					
Great Lakes					
MAM	AO(−), AMO(−)	NAO(+)			AMO(+)
Pacific Northwest					
JJA	PDO(−), AMO(−)	PDO(−)	Nino3.4(−), PDO(−), AMO(±)	Nino3.4(±)	
Lower Missouri					
JJA	AO(+)	AMO(−)			AMO(−)
SON					AO(+)
Upper Mississippi					
DJF		AMO(−)			

[a]See text for definition of the climate signals. A (+) indicates the positive phase of this index is significantly related to the runoff pattern (see section 2.5 for a description of the significance test), a (−) indicates the negative phase, and (±) indicates both phases. Rows indicate runoff season, and columns indicate lead time in seasons. DJF, December–February; MAM, March–May; JJA, June–August; SON, September–November; AMO, Atlantic Multidecadal Oscillation; AO, Arctic Oscillation; PDO, Pacific Decadal Oscillation; NAO, North Atlantic Oscillation; NP, North Pacific index.

Sources of hydrologic skill: long leads

Relationship of runoff at various leads and parts of North America to various climate patterns of variability.

There can be some enhanced predictability of future runoff from the current states of these patterns.

Not all patterns, nor even all phases of a pattern, provide predictability.

From Maurer et al., *Water Resources Research*, 2004, W09306.

Sources of hydrologic forecast skill: snow-water equivalent deviations

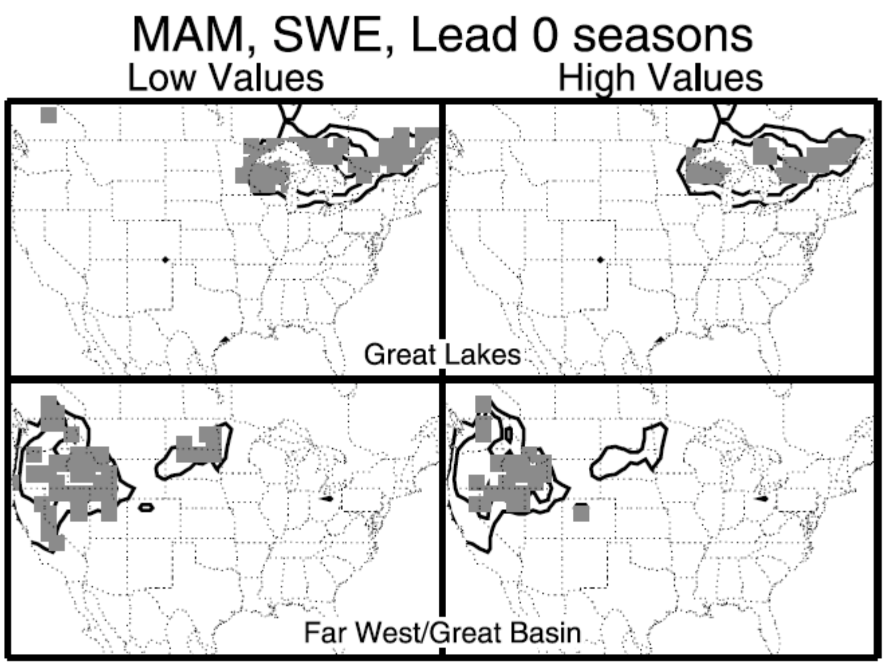
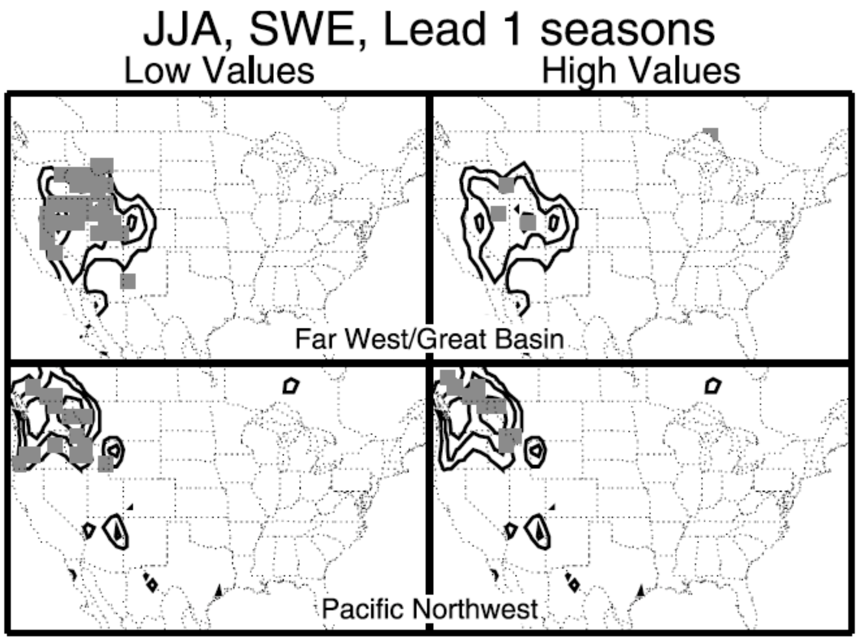


Figure 4. For the indicated runoff patterns (identical to those in Figure 3 for the specified season), shaded blocks indicate grid cells with statistically significant relationships of SWE with runoff pattern variability for the season March–May (MAM) and lead time of zero seasons. This relates the MAM runoff variability, expressed in the PC time series, with the SWE anomalies at the prior time indicated by the lead time.

- Contours: loadings associated with leading principal component for runoff in given area.
- Shaded area: grid cells with relationships of runoff and this PC.
- Conclusion: dry ground --> low runoff in spring season, snowy/wet ground, high runoff in spring season. Not surprising.

- Ref: Maurer et al. 2004.

Sources of hydrologic forecast skill: snow-water equivalent



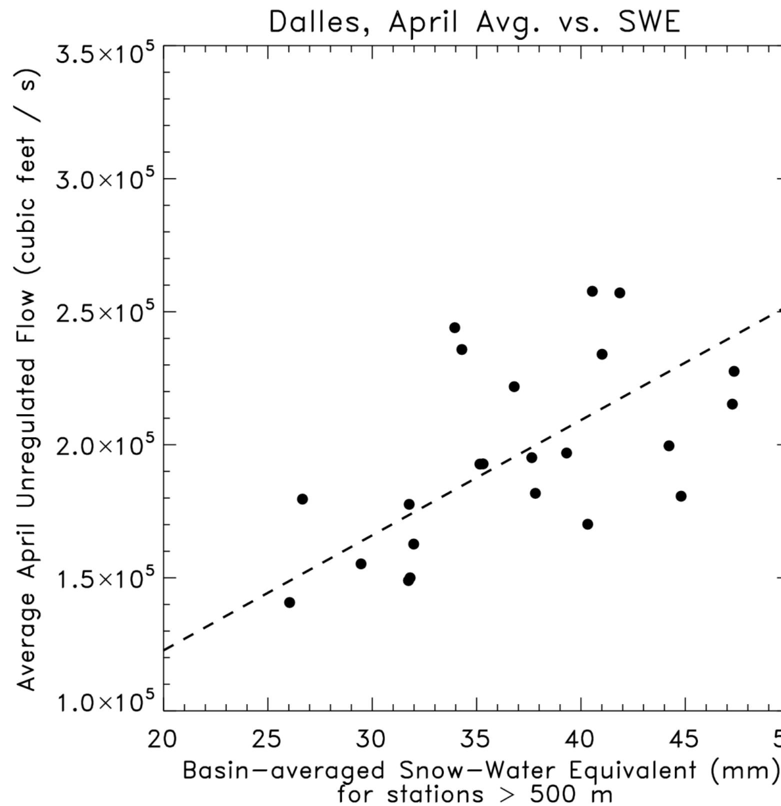
- Looking one season ahead, in western US, low spring snow cover --> low summer runoff. However, high spring snow cover in central US Rockies does not necessarily mean high summer runoff (presumably because the melting may have already occurred)

Past and present hydrologic forecast systems

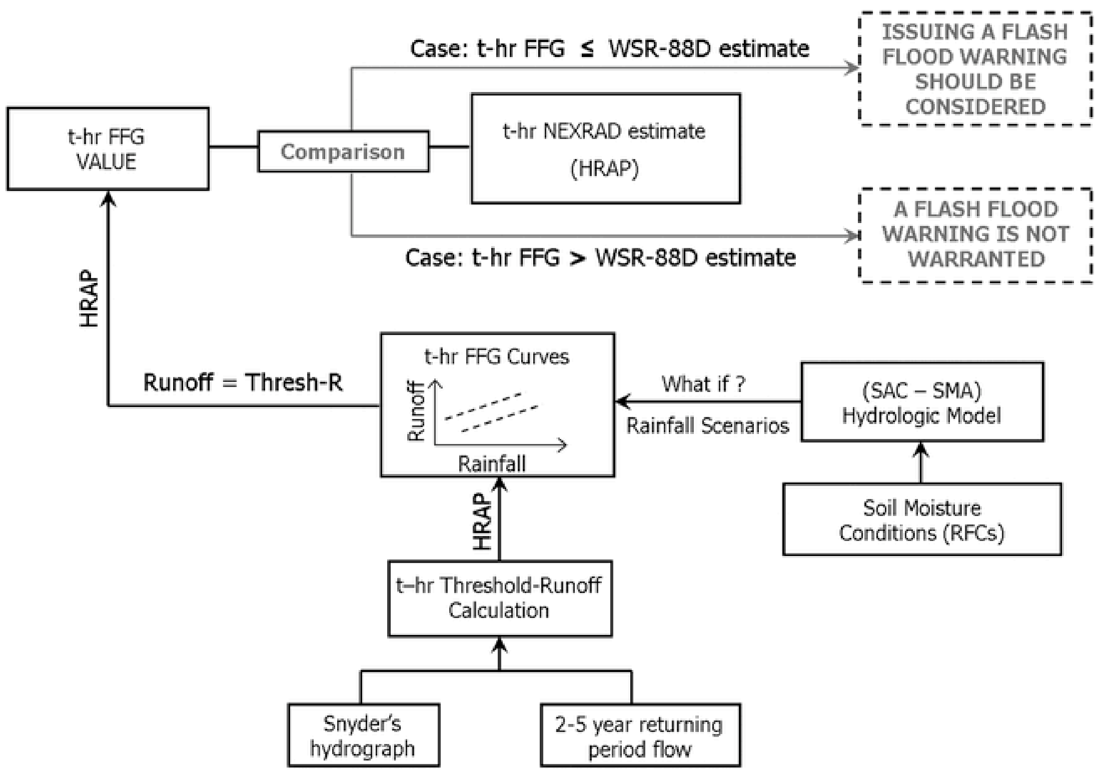
- Example 1: Regression method
- Example 2: US flash-flood warning system.
- Example 3: Ensemble streamflow prediction in US for seasonal forecasts.
- Example 4: Bangladesh medium-range probabilistic flood forecast system.
- Example 5: European short-range flood forecast system for small-medium basins.

(1) Regression models to predict streamflow

Example: predicting April maximum streamflow from Columbia-basin average 31 March snow-water equivalent



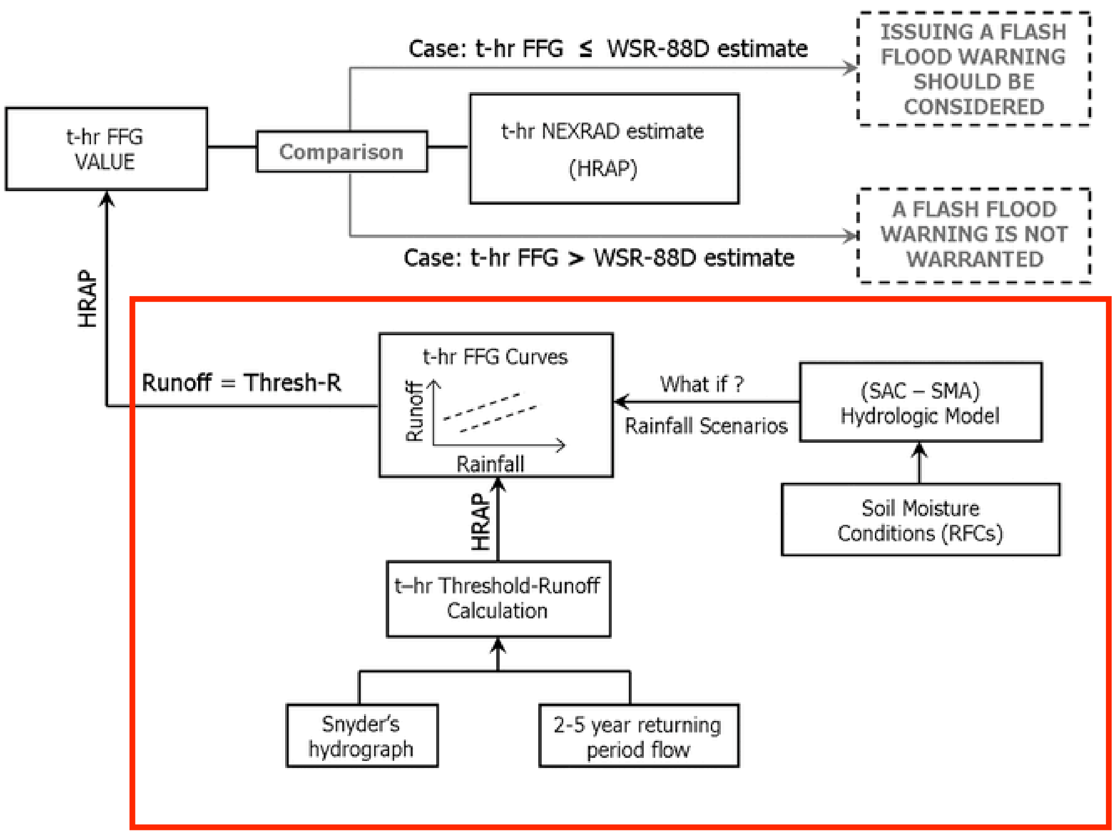
(2) Flash-flood warning system



- A sample system (here, the US River Forecast System) for flash-flood guidance in small basins.

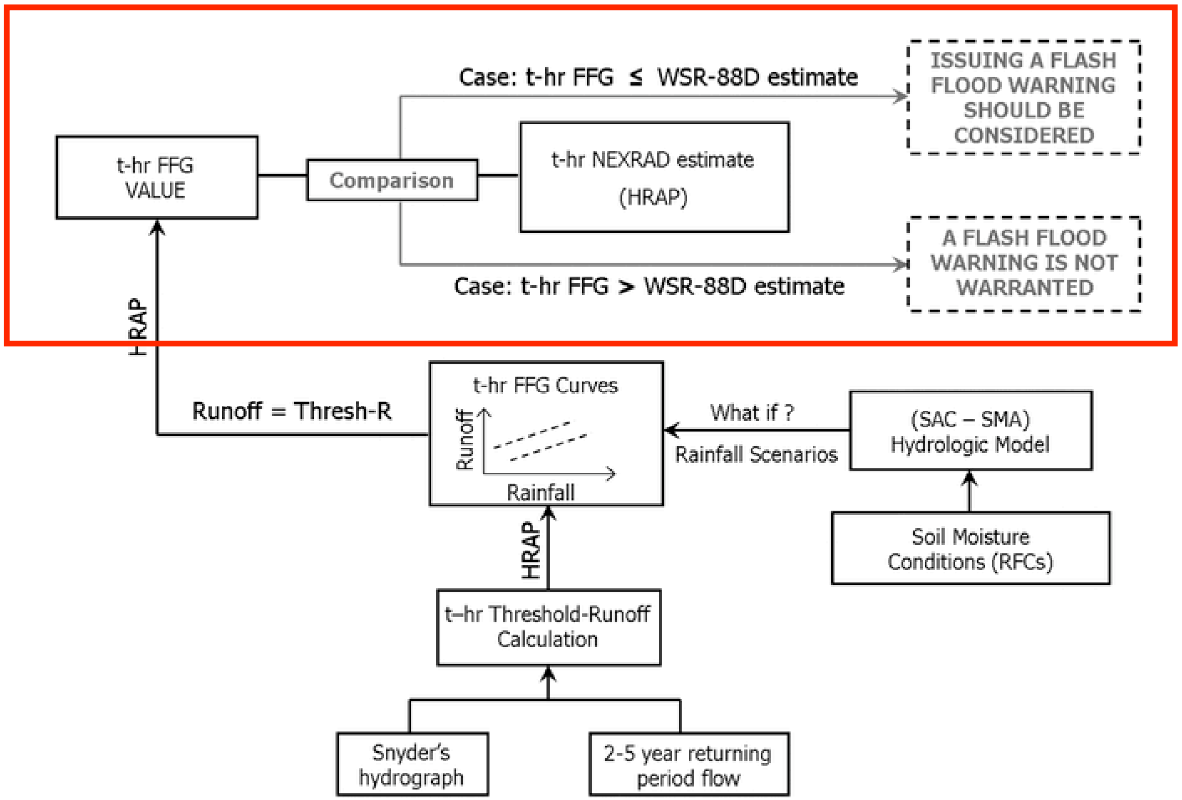
ref: Ntkelos et al, J. Hydrometeorology, Oct. 2006

(2) Flash-flood warning system



- Using geographic information system data, a hydrologic model, and a variety of land-state conditions, tables of the time-averaged amount of precipitation needed to cause a flash flood are tabulated for a small basin/ For example, if today's soil is wet and there is more than 20 mm/hour * 6 hours, the basin will flood.

(2) Flash-flood warning system

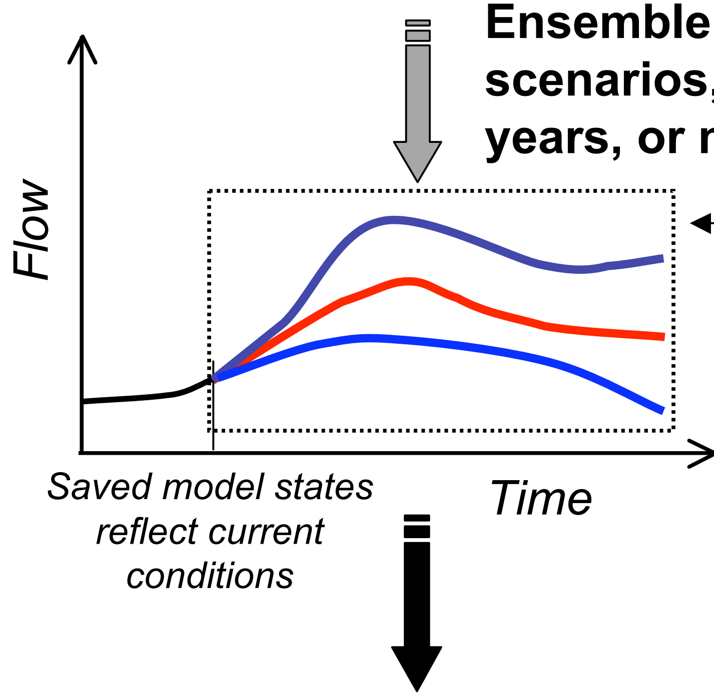


- Precipitation estimated from radar scans is compared with the estimated precipitation rates that will produce a flood to determine whether a warning should be issued.

(3) US ensemble streamflow prediction (ESP) technique (medium to long leads)

Multiple streamflow scenarios with historic meteorological or forecast weather/climatic data

Ensemble of time series of possible scenarios, commonly weather in past years, or model forecasts

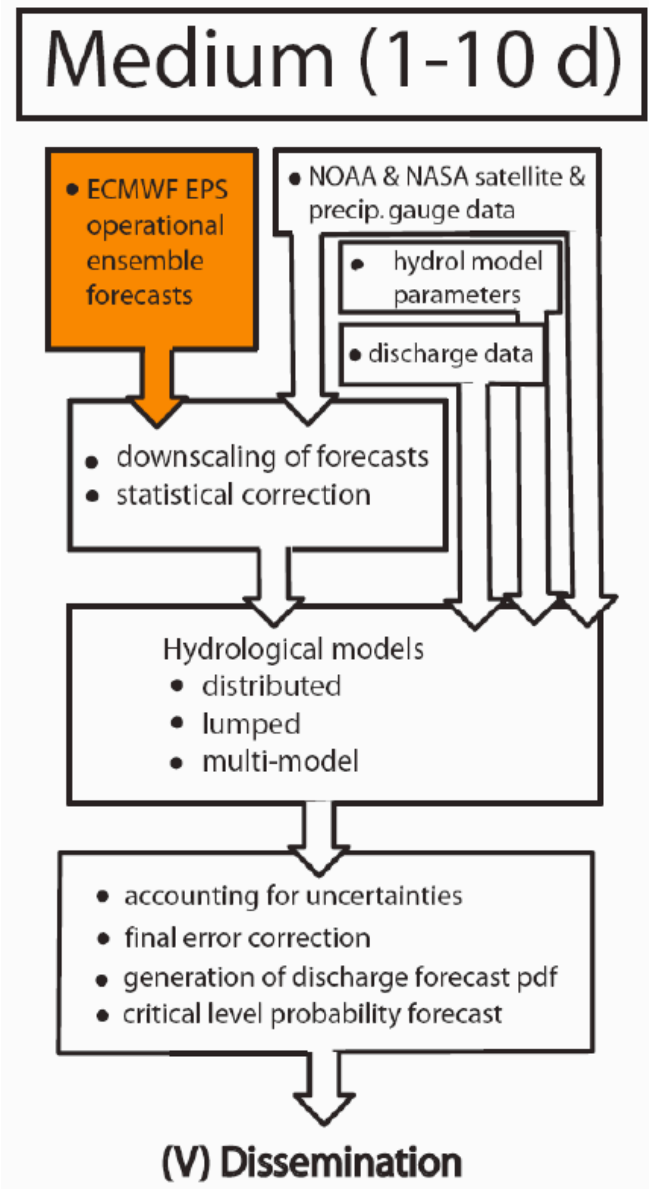


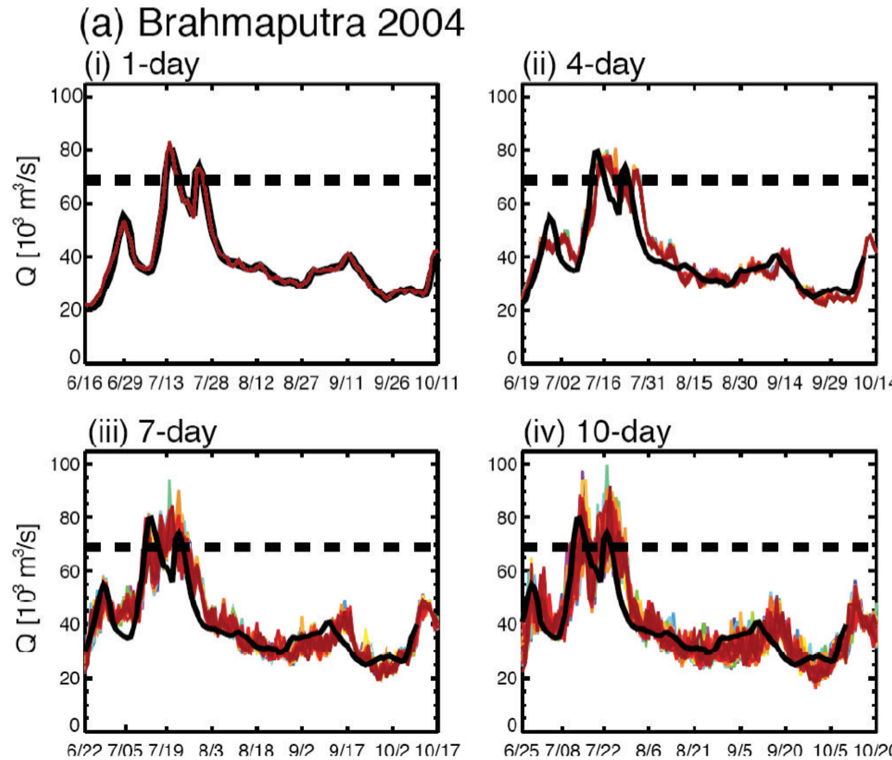
Scenario 2
Scenario 1
Scenario 3

Hydrologic forecast model using initial model state and atmospheric ensemble

Results used in statistical analysis to produce forecasts with probabilistic values

(4) Bangladesh flood forecast system





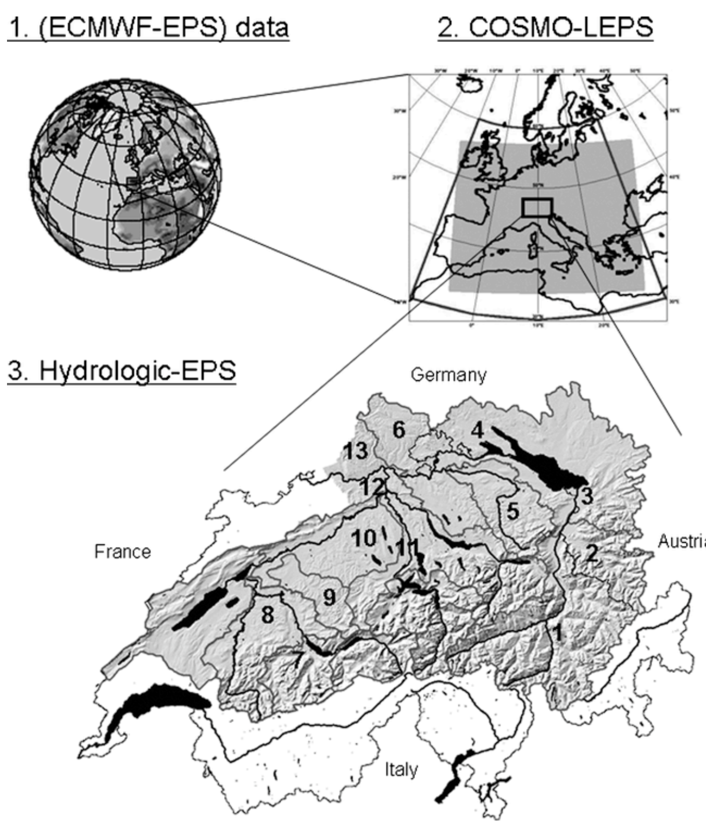
black = observed, red=ensemble

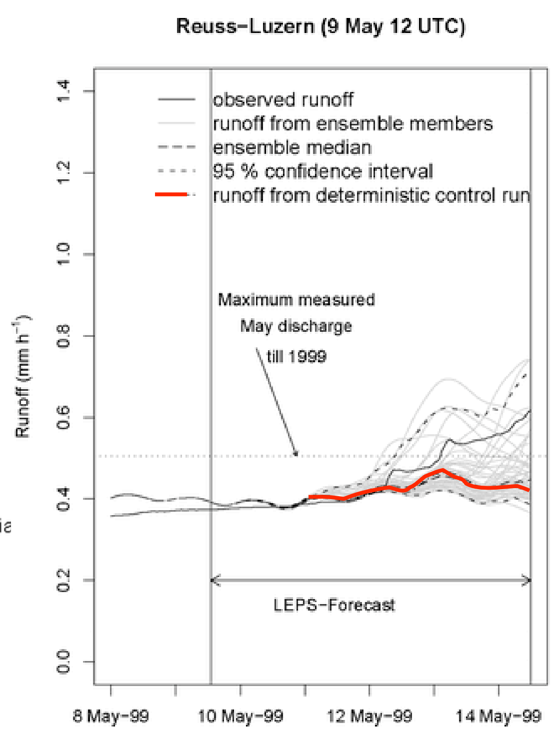
Tom Hopson and Peter Webster's ensemble-based flood forecast system using ECMWF forecast data. Bangladesh is very flat country, prone to flooding.

Ref: Hopson and Webster, 2008, in review.

(5) Short-term flood forecasting with hydrologic model driven by local-area ensemble forecasts

- COSMO-LEPS limited-area ensemble driving hydrologic forecast model.

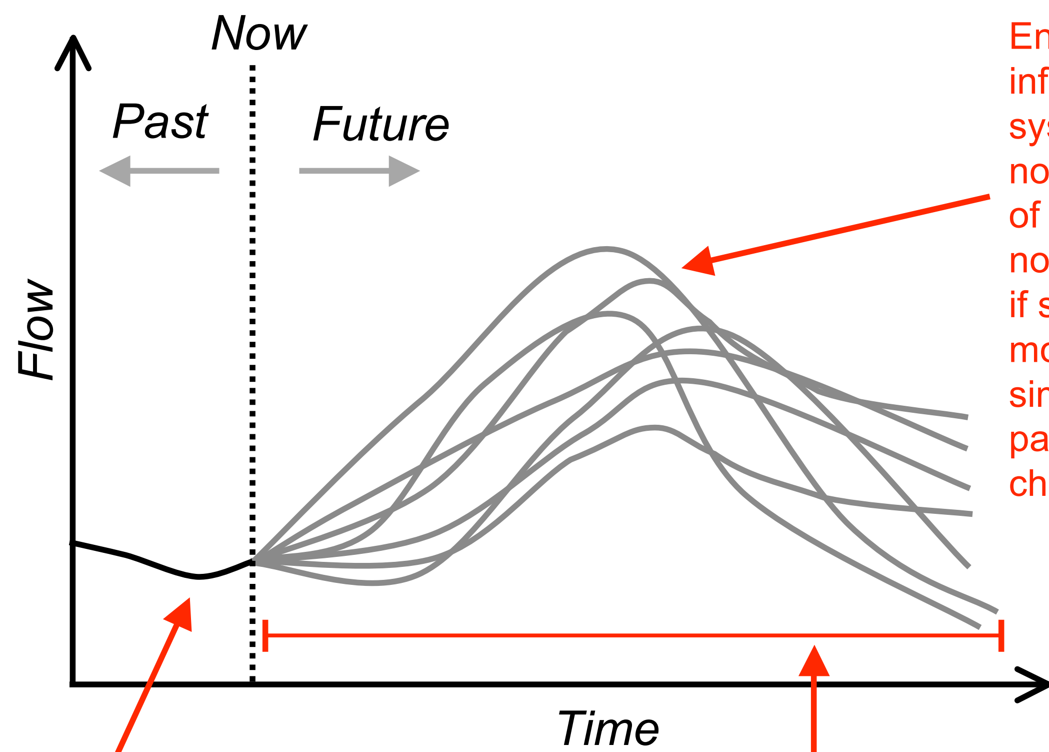




At the start of this flood event, driving the hydrologic model with a deterministic forecast produced non-record flood forecasts. Some of the ensemble members did produce record flooding, as was observed.

Verbunt et al., August 2007 *J. Hydrometeorology*

Deficiencies of many 1st-generation coupled hydrologic forecast systems



Ensembles of atmospheric information driving hydrologic system may be biased, may not represent all sources of forecast uncertainty, may not have needed spatial detail if supplied from numerical model(s). For long-lead simulations, samples of past years may not represent changing climate.

Soil moisture, snow cover, streamflow are not known perfectly at all locations. What is their uncertainty? How do errors spatially co-vary?

A hydrologic forecast model is run during this time, keeping track of streamflow changes. Such models are far from perfect, sources of model error may not be accounted for.

IN BOX
INSIGHTS and INNOVATIONS

HEPEX

The Hydrological Ensemble Prediction Experiment

BY JOHN C. SCHAAKE, THOMAS M. HAMILL, ROBERTO BUIZZA, AND MARTYN CLARK

A RATIONALE FOR HYDROLOGICAL ENSEMBLE PREDICTION. Imagine yourself as the manager of a reservoir in the western United States. Finally, after many years of drought and low water levels, the mountains above you have received ample snowfall this winter. It is now late spring, and the extended-range forecast suggests a strong surge of moisture. A single forecast based on a (possibly high-resolution) model prediction indicates heavy rain on the snowpack, causing very rapid melting, perhaps producing more flow than your reservoir can store. If you release water from the reservoir now in anticipation of extreme runoff and the precipitation is less than predicted, that water is lost to your customers; should the drought return, inadequate reservoir storage may eventually require water rationing. But if you do not release, there is a chance that the sudden surge of water could top the reservoir and cause potentially catastrophic flooding downstream.

This is an example of one of many complex decisions faced by water managers. Ideally, as manager, you would be supplied with a perfect weather forecast, you would have precise measurements of the snowpack and soil moisture, and you would utilize highly engineered hydrological models that would nearly perfectly predict the amount and timing of the streamflow. The one resulting hydrological prediction would provide enough information to make the correct decision. In reality, there are tremendous uncertainties. The weather forecasts supplied to you are imperfect and lacking in critical detail; will the precipitation fall primarily in the form of rain on snow (bad, as it may cause flash flooding) versus snow on snow (good, as it would generate a gradual, delayed runoff)? At what elevation will the rain change to snow? And what about the existing snowpack? There may be only a handful of actual snow-depth measurements. Finally, the land surface and hydrological routing models you have available are commonly simplified descriptions of the hydrological processes; for example, they may treat each subbasin as a homogeneous element covered by the same average snow cover and soil moisture. Given the myriad uncertainties, a natural tool for making the decisions would be a probabilistic forecast, possibly based on an ensemble hydrological prediction system, akin to the now-ubiquitous ensemble weather prediction systems. Ideally, this system would produce multiple realizations of possible future streamflows that were "sharp" (much more specific than, say, drawing from a climatology of streamflows in past years) and yet reliable (e.g., over many situations, when there was a 20% forecast of a runoff exceeding y m^3 s^{-1}, the runoff actually exceeded y m^3 s^{-1} 20% of the time). Were such a product available, the eventual cost of reduced storage from a dam release could be weighed against the likelihood of flooding impacts without the release.

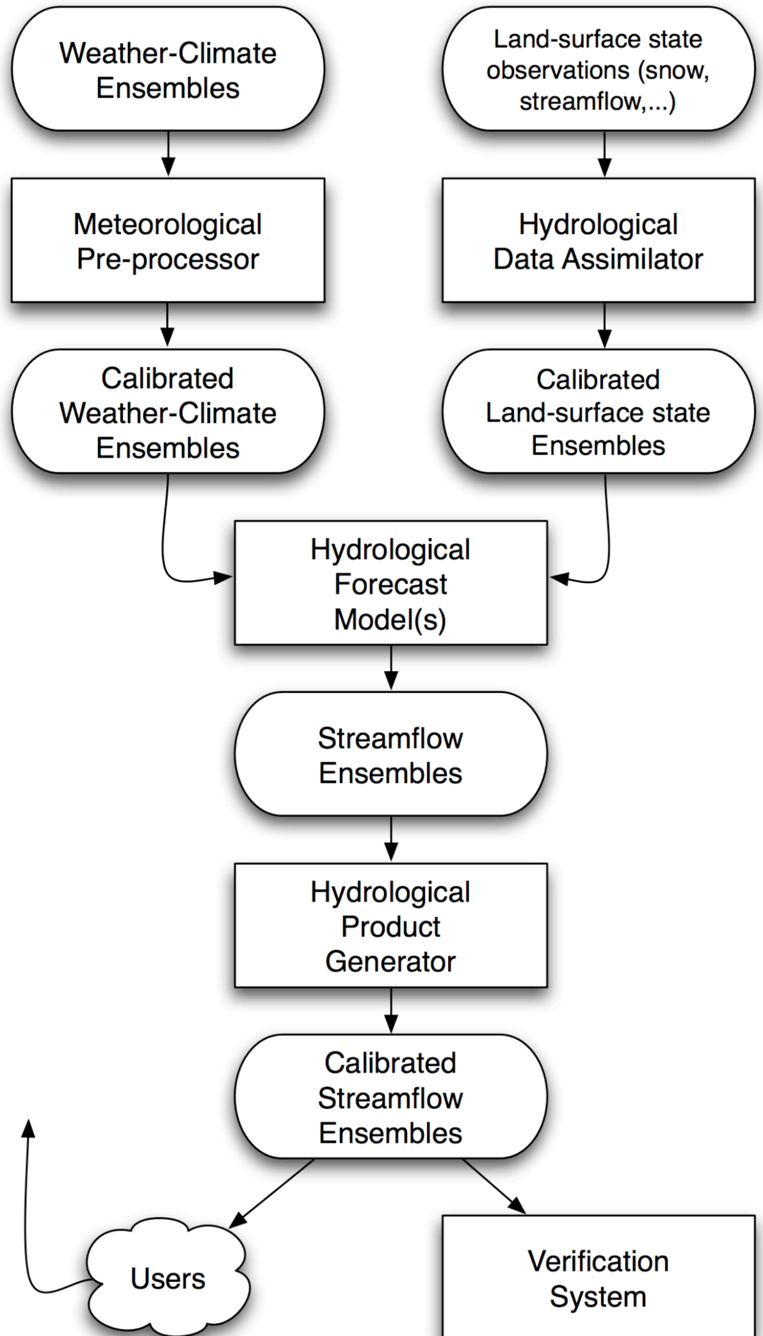
An automated, skillful, reliable ensemble streamflow forecast product is conceptually appealing. Figure 1 provides a schematic of one possible system that explicitly accounts for the major sources of uncertainty in the forecasting process. An ensemble of atmospheric forecasts is first run through a meteorological preprocessor, producing meteorological forcings for the hydrological model that have been downscaled, corrected for bias, converted to produce the specific variables of interest, and adjusted to have realistic spatial and temporal correlations of errors.

AFFILIATIONS: SCHAAKE—Consultant, NOAA National Weather Service, Office of Hydrologic Development, Silver Spring, Maryland; HAMILL—NOAA Earth System Research Laboratory, Physical Sciences Division, Boulder, Colorado; BUIZZA—European Centre for Medium Range Weather Forecasts, Reading, England; CLARK—National Institute for Water and Atmospheric Research, Christchurch, New Zealand
CORRESPONDING AUTHOR: Dr. John C. Schaake, 1A3 Spa Creek Landing, Annapolis, MD 21403
E-mail: john.schaake@noaa.gov

DOI:10.1175/BAMS-88-10-1541

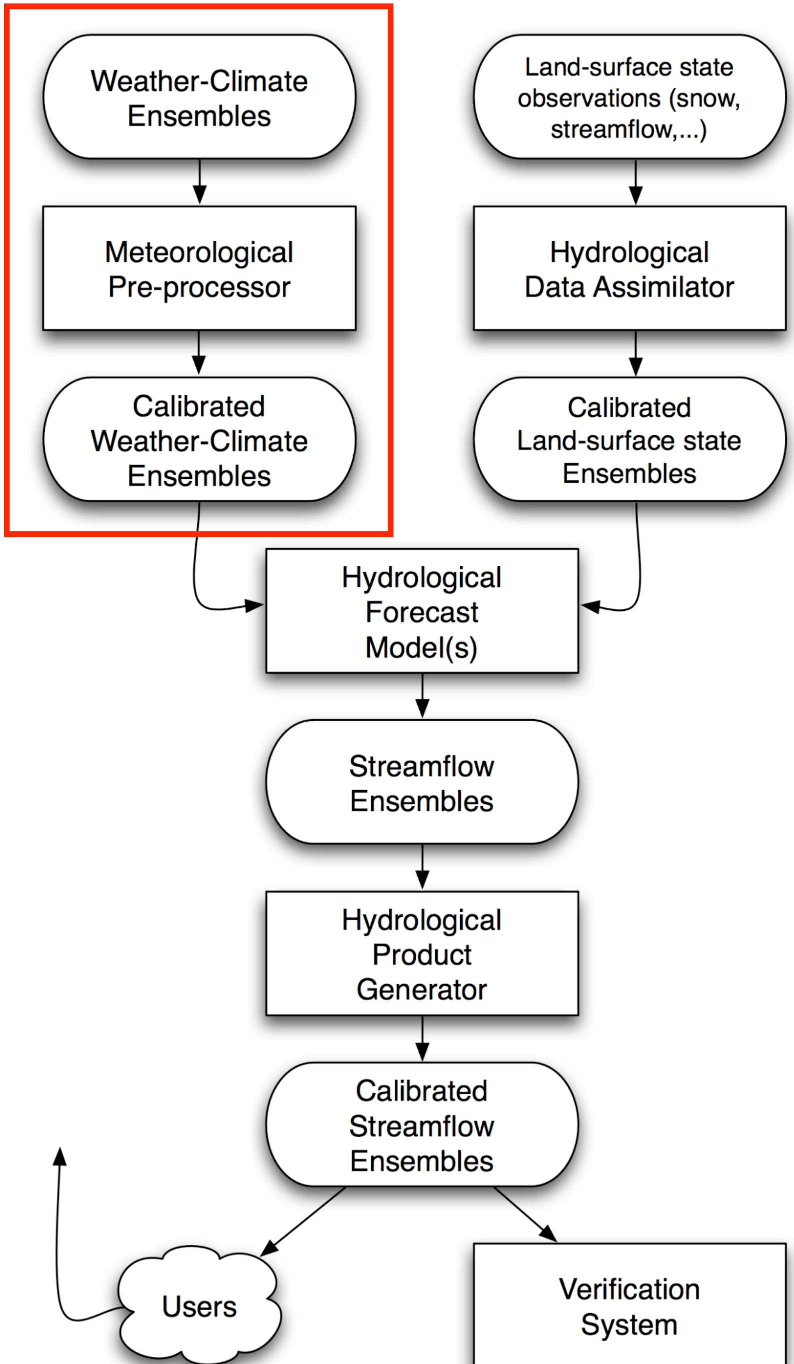
"HEPEX"

an international, cooperative project to advance ensemble hydrologic predictions



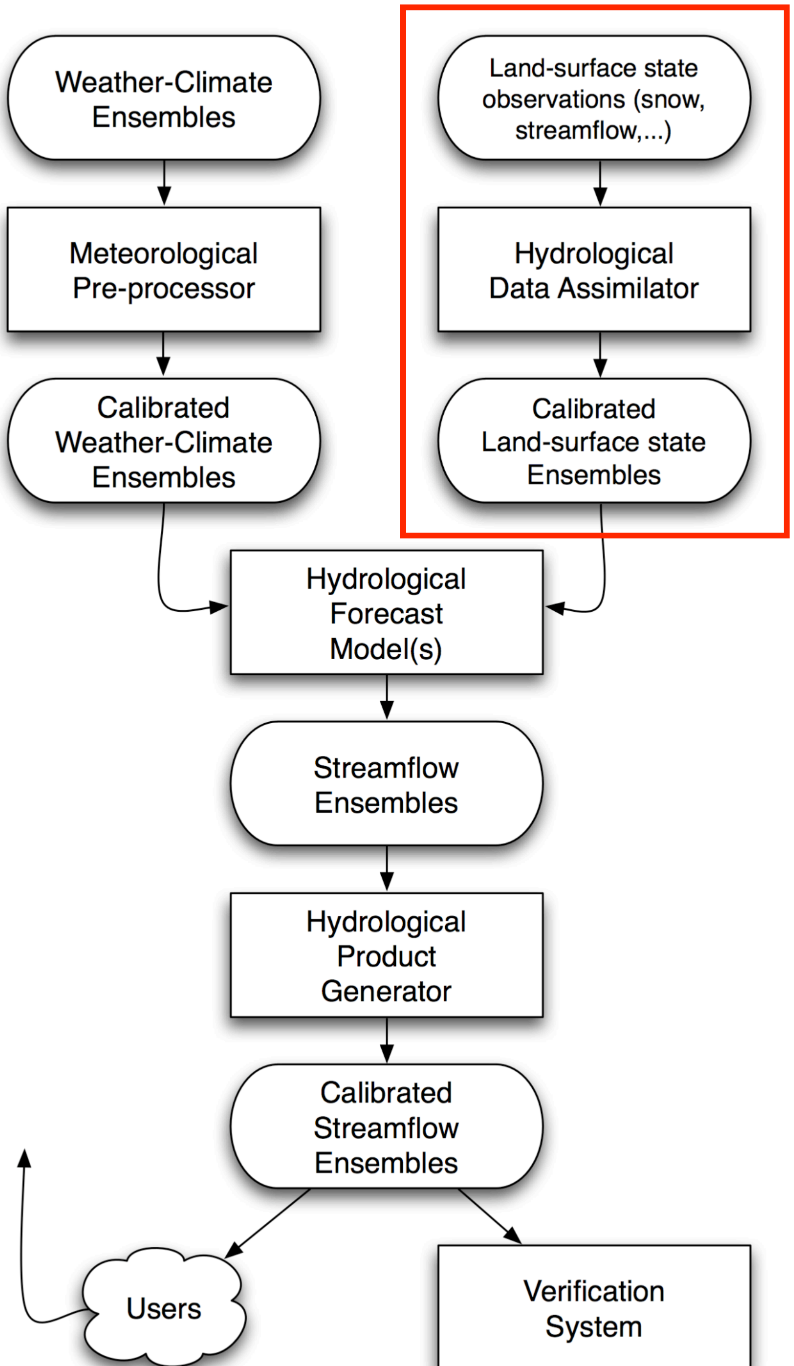
HEPEX's envisioned

"Ensemble Hydrological Prediction System"

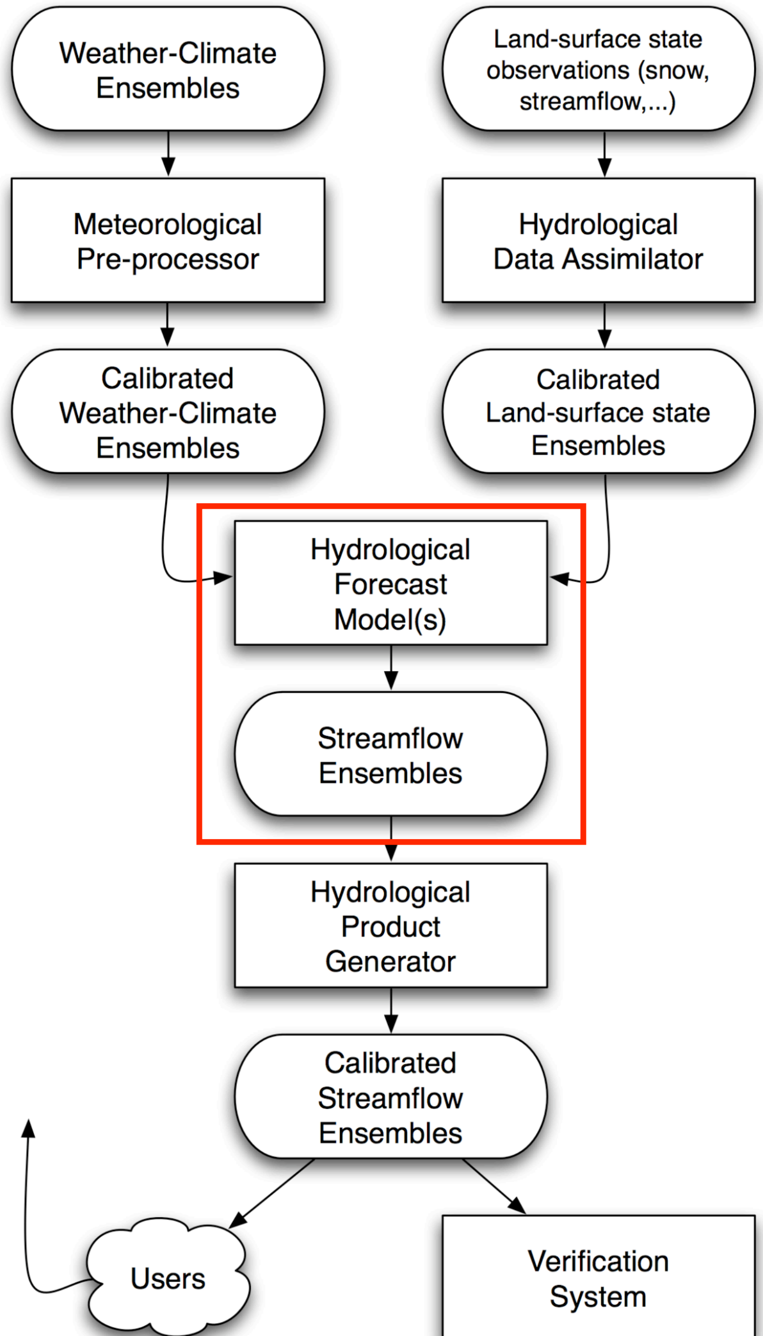


Use ensembles
of statistically adjusted
weather / climate forecasts
to provide
samples of future
atmospheric states

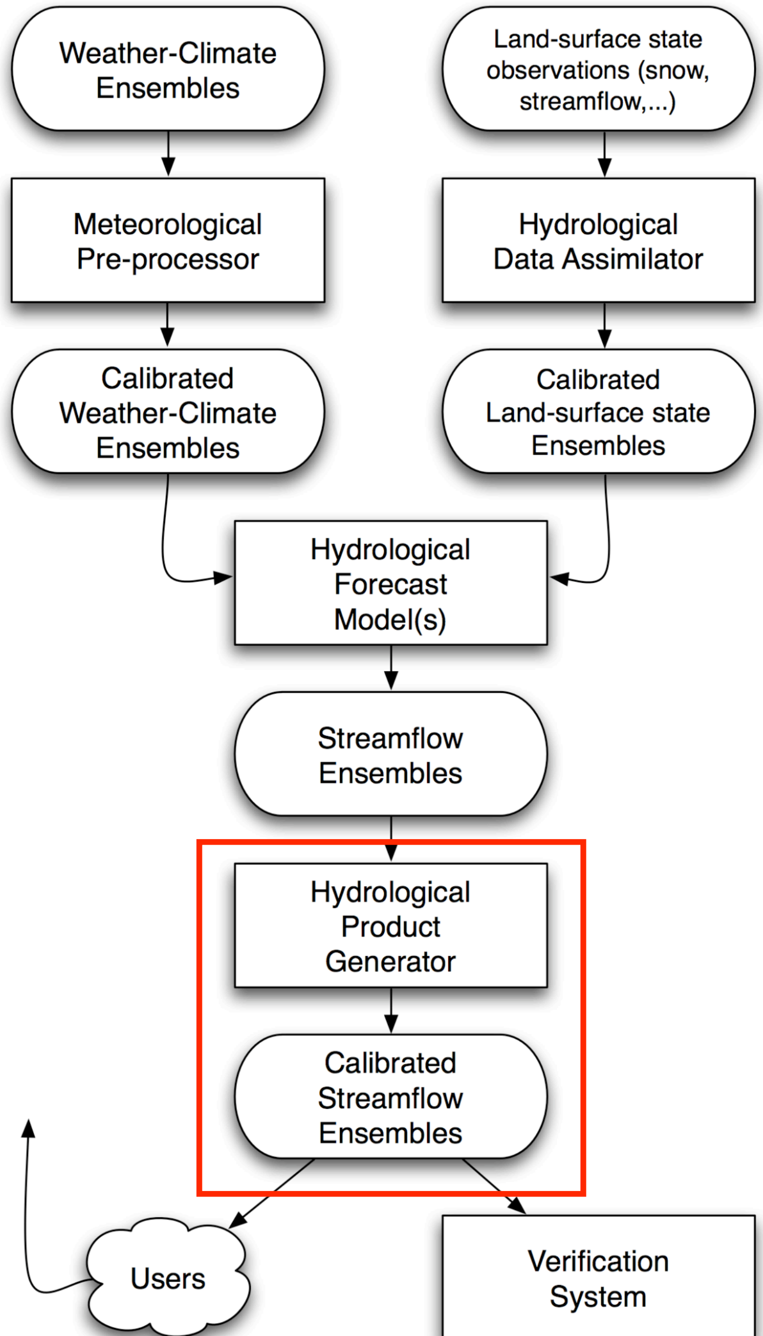
<u>Important properties</u>:
(1) appropriately skillful
at short leads
(2) representative of this year's
climate if forecasts extend to
longer leads
(3) calibrated data has
biases removed, correct
spatial covariances.



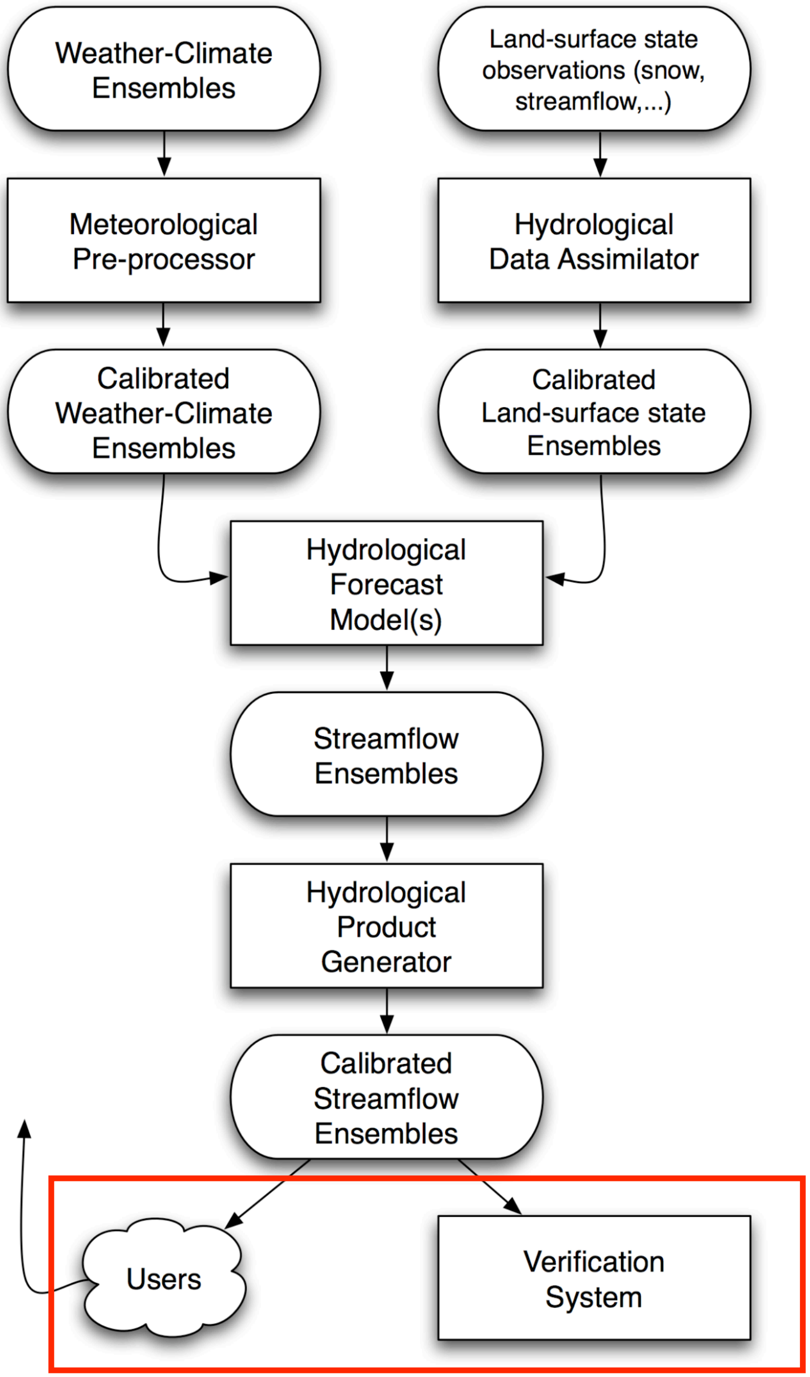
Develop an *ensemble* of initial land / snow/ streamflow states consistent with the observational data, with appropriate spread and error covariances.



Input the weather-climate ensembles and land / snow / streamflow ensembles into hydrologic forecast model(s), with multiple parameters or stochastic formulations to account for model uncertainty.

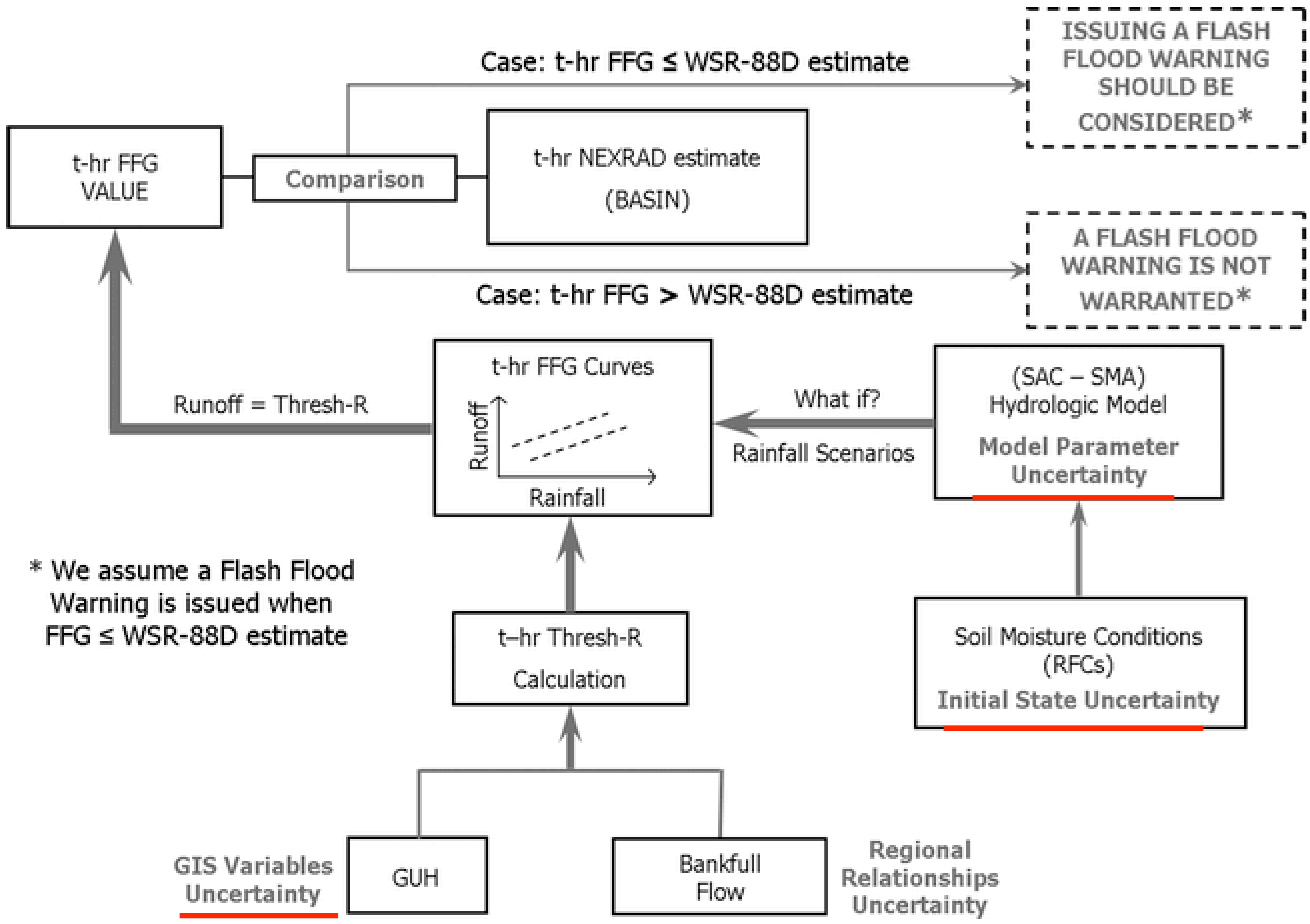


Statistically adjust the streamflow forecasts, mitigating the remaining biases/spread issues, and tailoring the products to the formats most useful to the customers.



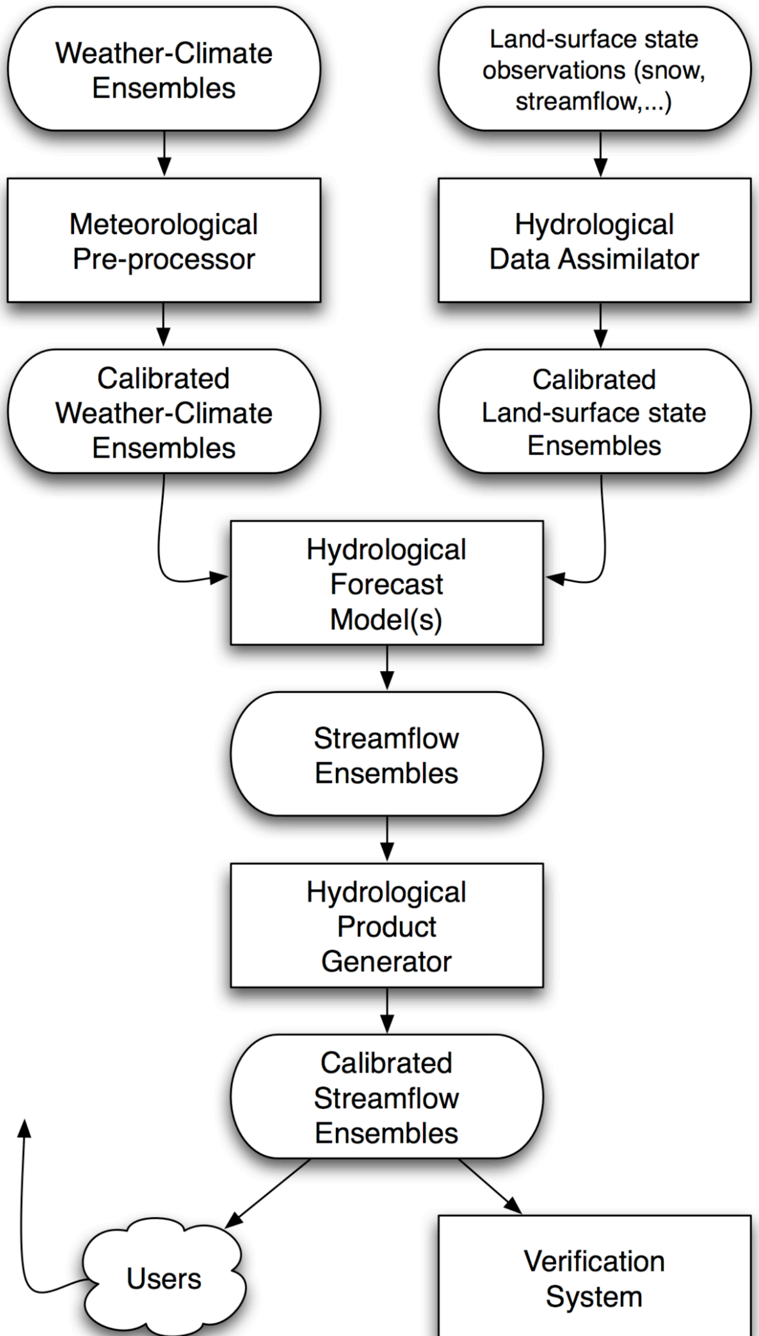
Monitor the forecasts, monitor the users' issues, and refine the process.

Probabilistic systems can be developed for flash flood warnings, also



proposed revision of the flash-flood warning system discussed earlier.

ref: Ntkelos et al, J. Hydrometeorology, Oct. 2006

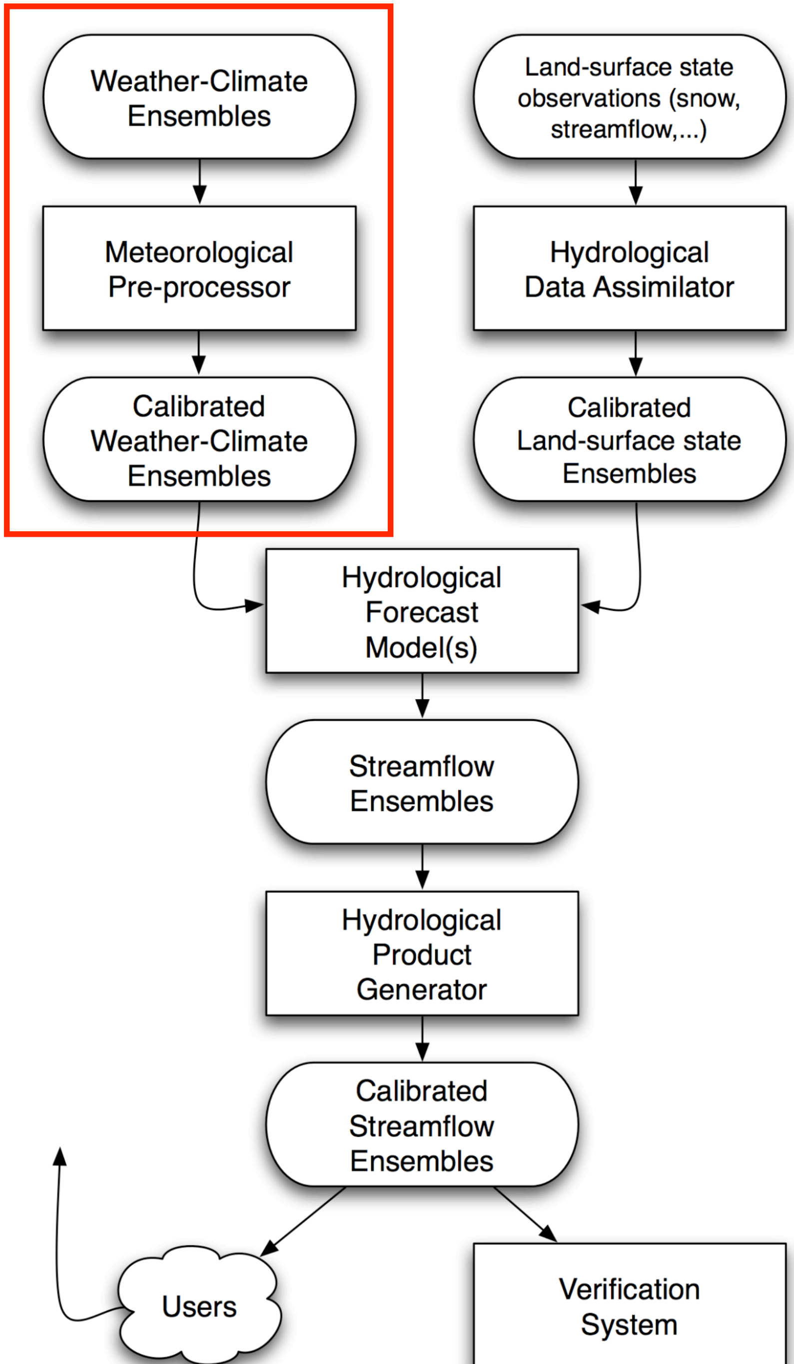


HEPEX idea, again.

Nice in concept.

(1) What is the state of development of such a system?

(2) What are the technological hurdles in the way of making these sorts of systems really well calibrated and useful to decision makers?



Generating calibrated weather-climate ensembles

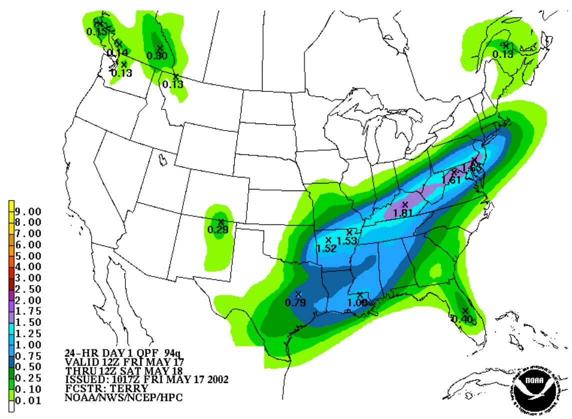
Simple: pre-adjustment system

Historical temperatures and precipitation → Pre-adjustment system → Adjusted temperatures and precipitation

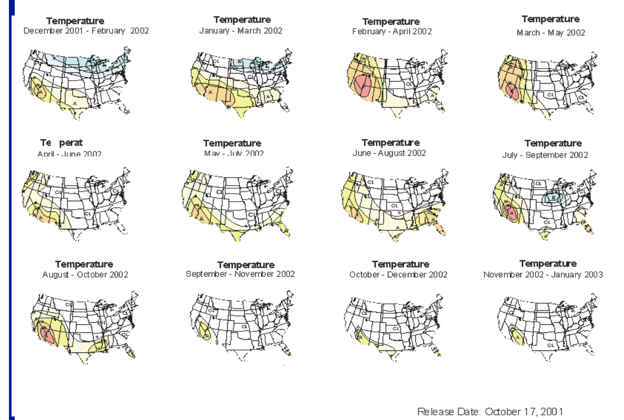
Weather forecasts → Pre-adjustment system

Climate forecasts → Pre-adjustment system

Weather forecasts

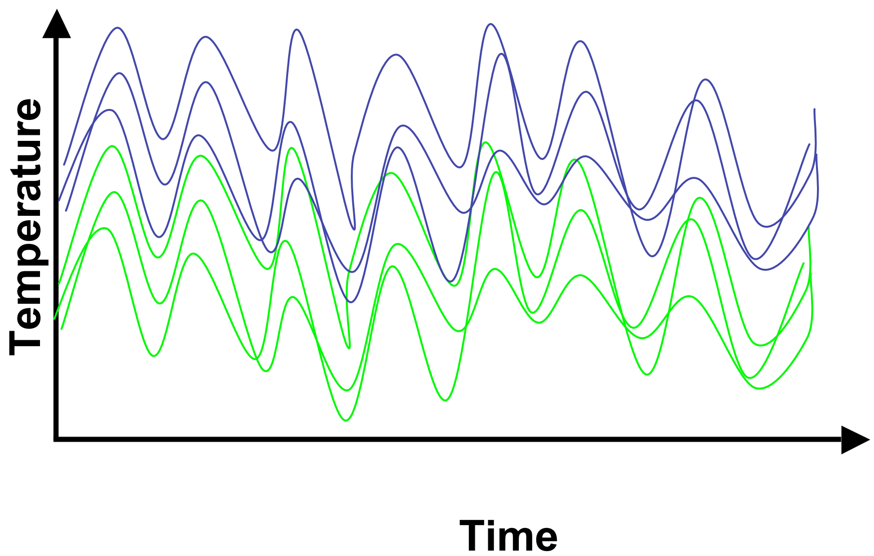


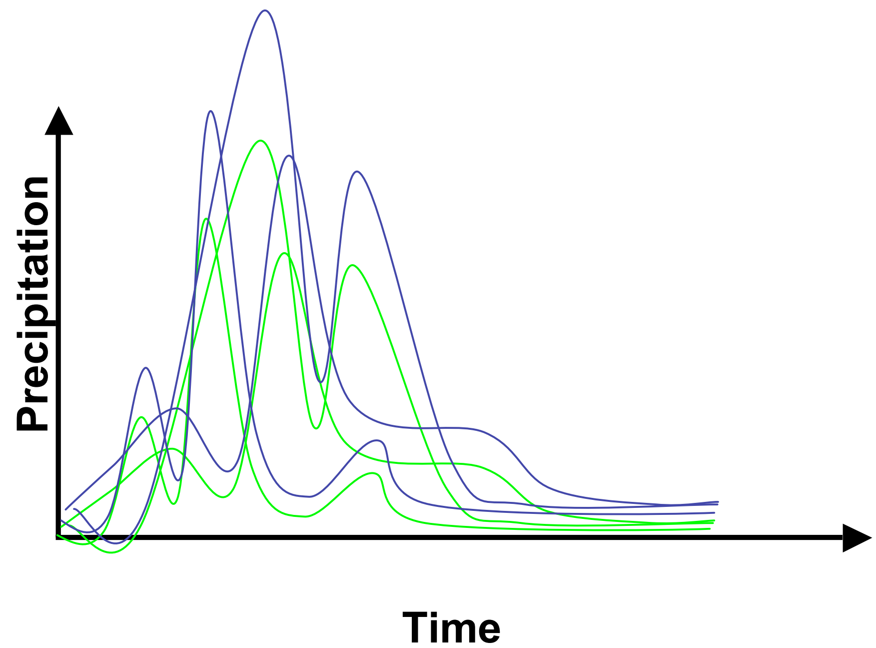
Climate forecasts



c/o Kevin Werner, NOAA/NWS, and COMET

Pre-adjustment method





Temperature Ensemble

Precipitation Ensemble

Adjusted Temperature ensemble based on a CPC "warm" probability shift.

Additive adjustment

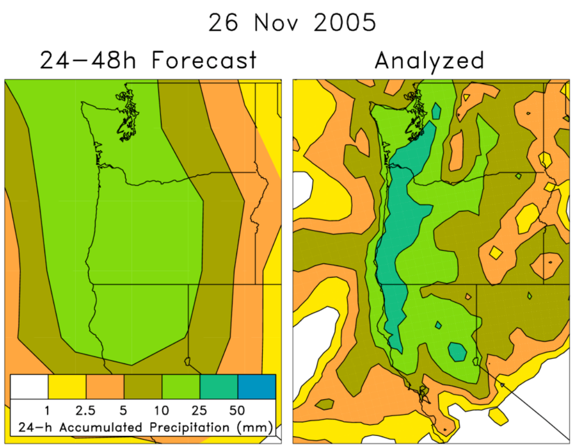
Adjusted Precipitation ensemble based on a CPC "wet" probability shift

Multiplicative adjustment

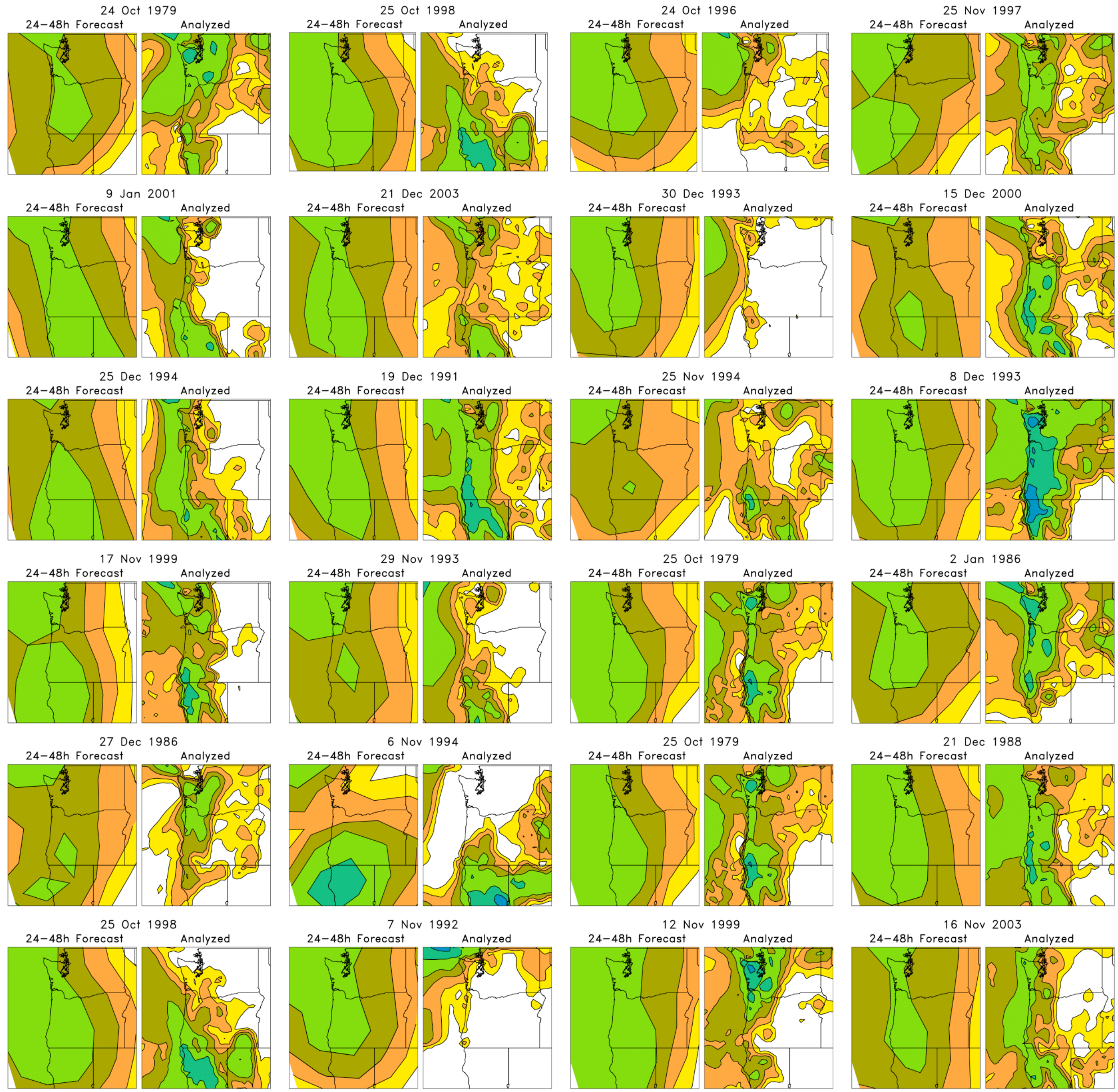
c/o Kevin Werner, NOAA/NWS, and COMET

Coarse model-forecast data are not downscaled,
i.e, adjusted to have correct space-time variability.

Dealing with ensemble forecast deficiencies: analogs using reforecasts

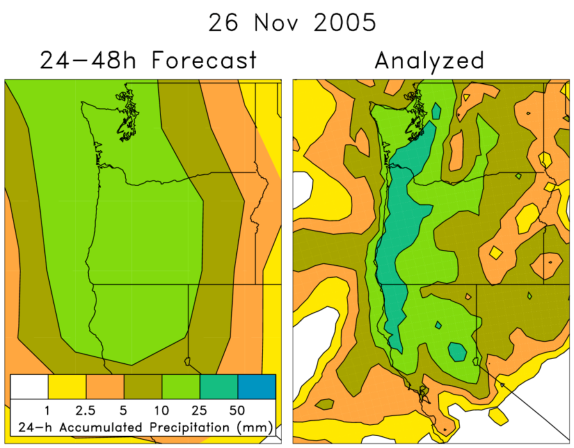


On the left are old forecasts similar to today's ensemble-mean forecast. For feeding ensemble streamflow model, form an ensemble from the accompanying analyzed weather on the right-hand side.



Hamill and Whitaker, Nov. 2006 MWR.

Dealing with ensemble forecast deficiencies: analogs using reforecasts



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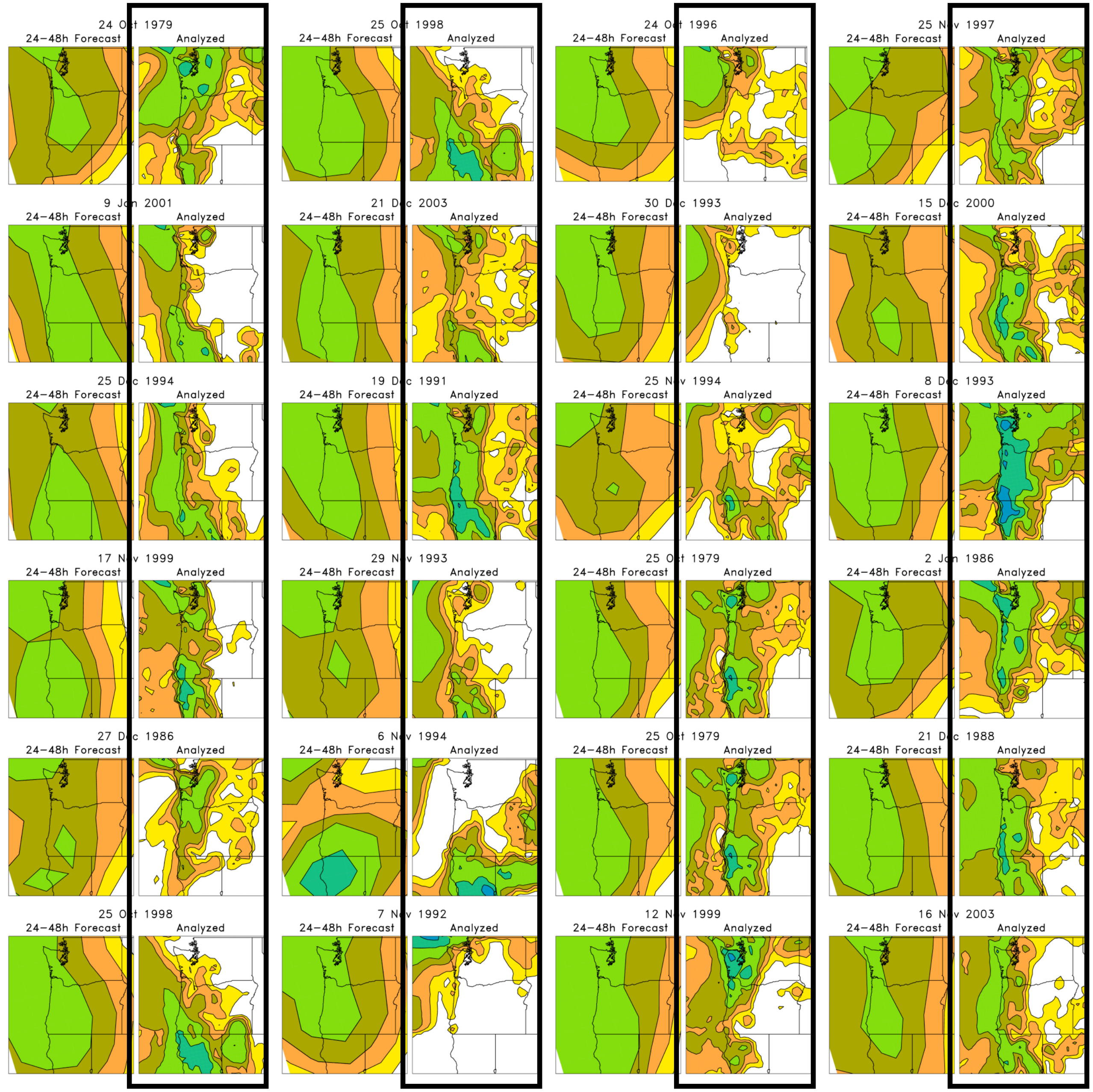
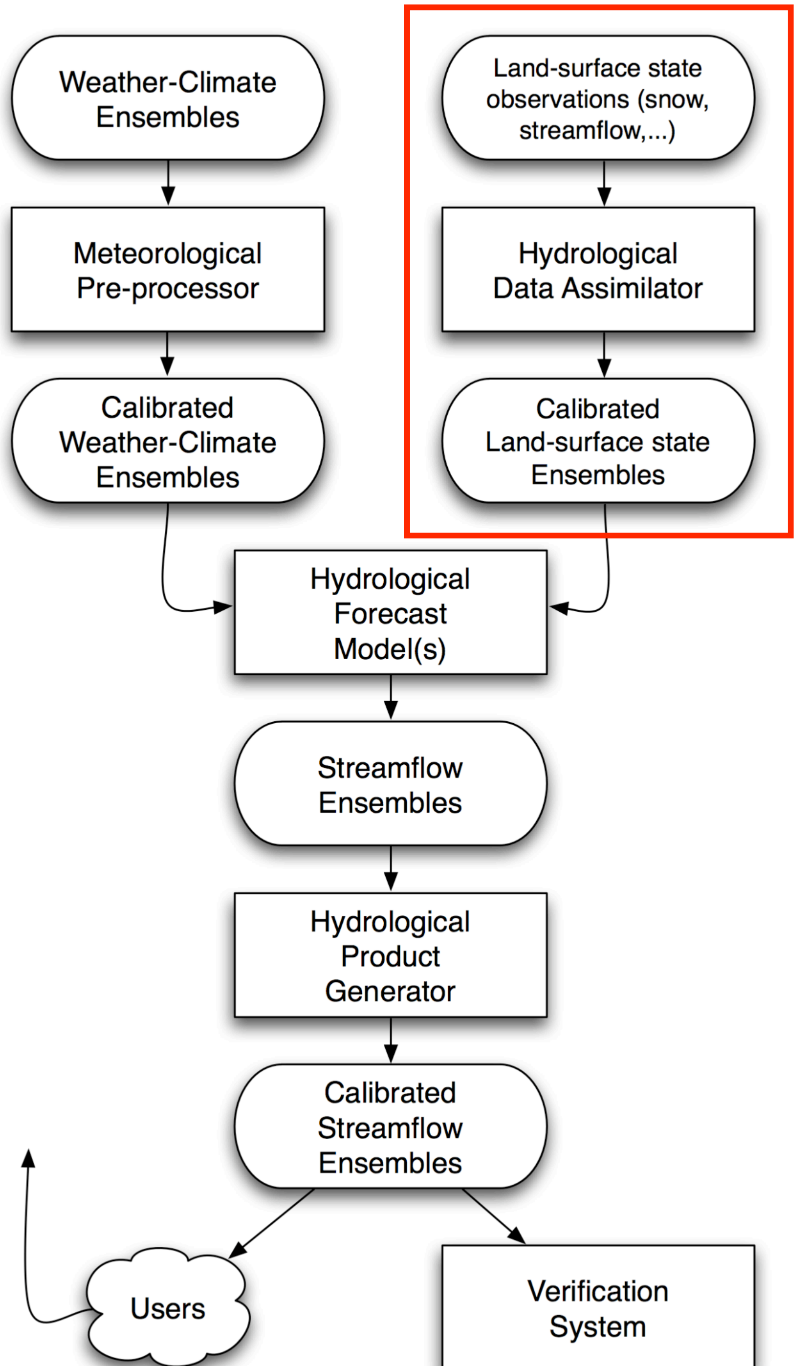
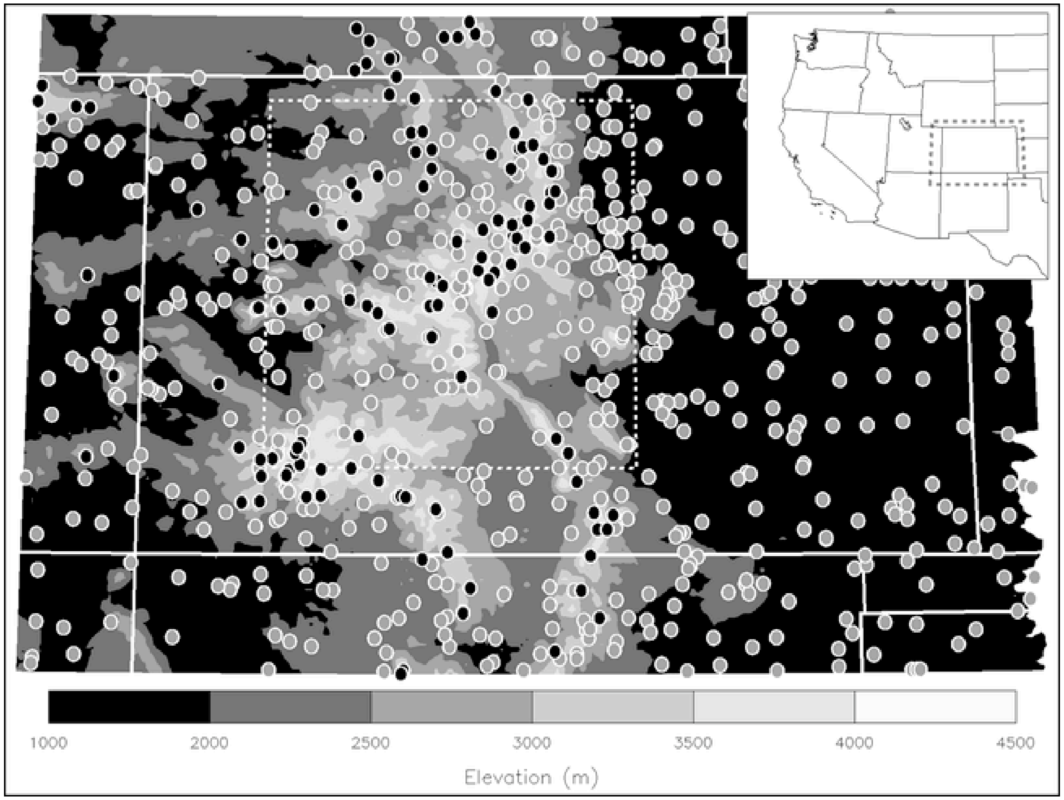




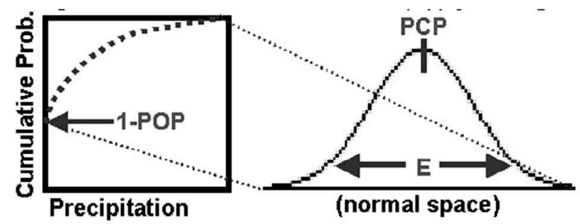
Develop an *ensemble* of initial land / snow / soil moisture / streamflow states consistent with the observational data, with appropriate spread and error covariances.

Example: probabilistic quantitative precipitation estimation in complex terrain



- Would like to define a gridded ensemble of possible precipitation analyses in a region. This would provide forcings for a land-surface analysis.
- Ensemble should have the right uncertainty (spread, spatial covariances).
- Proposed solution:

(1) Compute climatological CDF using past observations. Use this CDF to define transformation to Gaussian

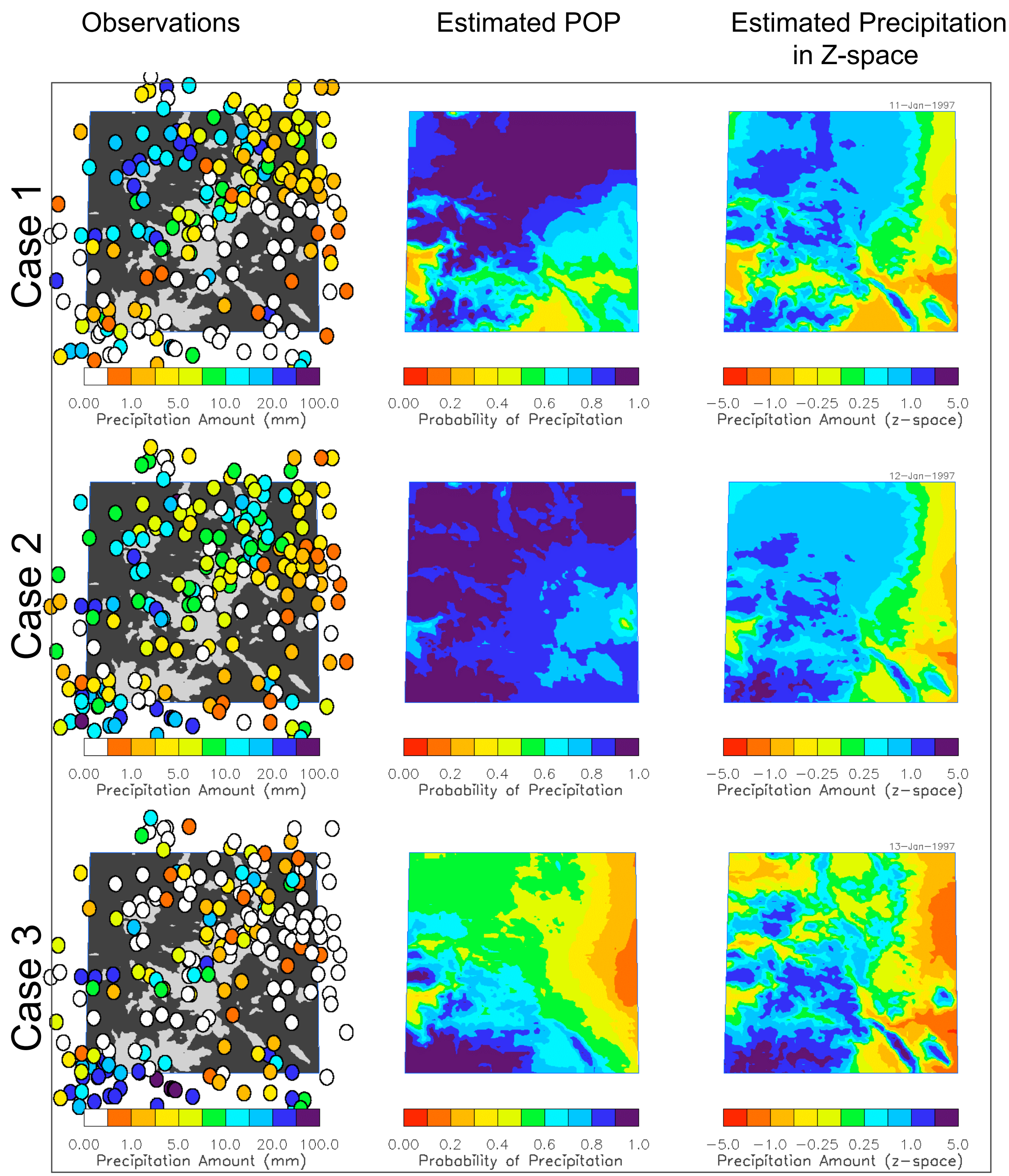


(2)Using today's available observations (dots), estimate conditional CDF of precipitation through regression analysis.

(3) Generate ensembles from correlated random fields to sample from the gridded precipitation CDFs.

ref: Clark and Slater, Feb. 2006 *J. Hydrometeorology.*

[more]

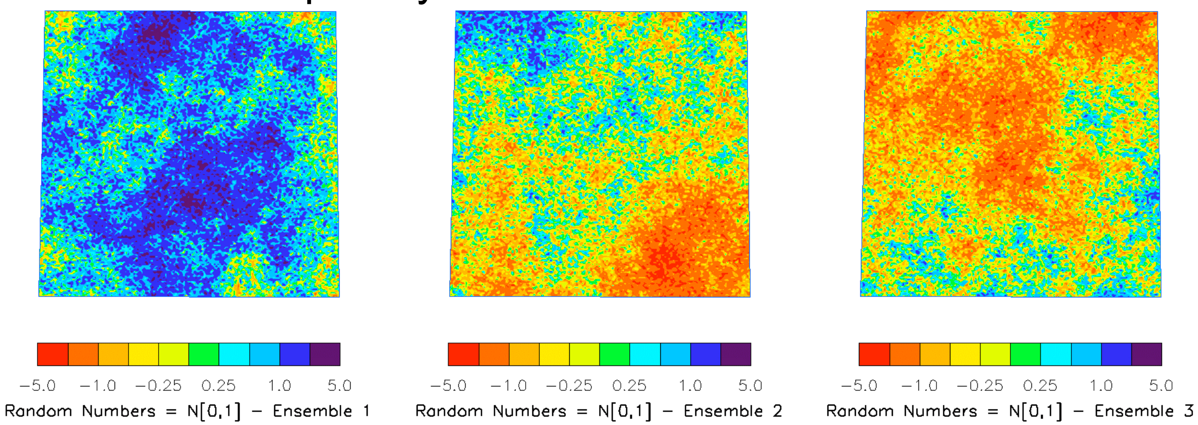


From stations to POPs and normalized precipitation amount.

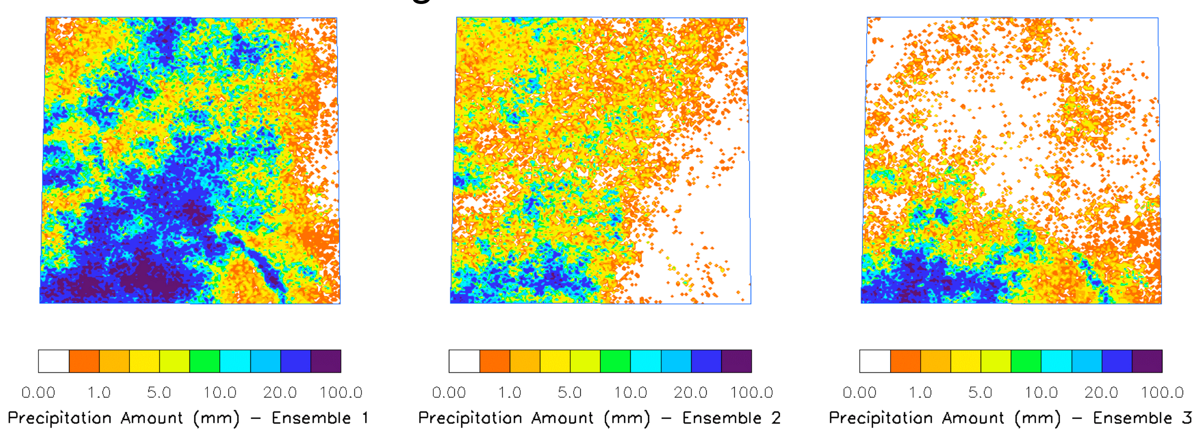
- At each grid point, perform weighted regression based on factors such as distance, similarity in elevation. Precipitation data is converted to normal distributions.
- Shown here: observations, regression-estimated POP, and estimated normalized precipitation amount for three different days, with the right-hand column representing the mean of the CDF in normalized coordinates appropriate to each grid point. Not shown: an estimate of the analysis error in Z-space.

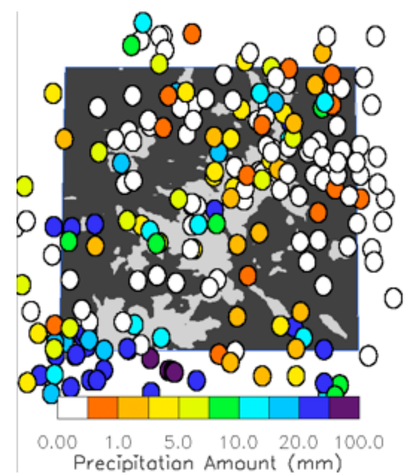
Generating ensembles from correlated random fields to sample from the gridded precipitation CDFs.

1. Construct spatially correlated fields of random numbers



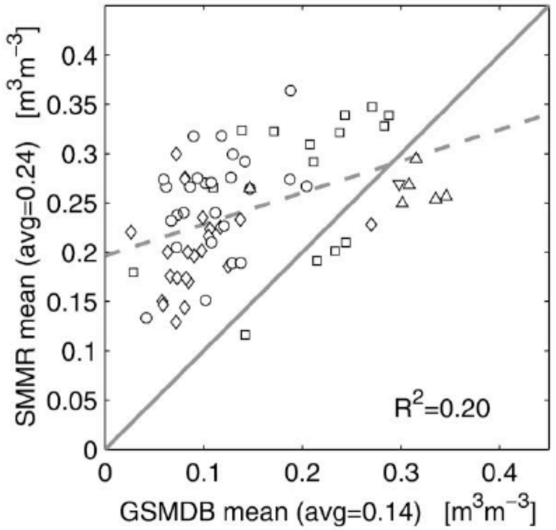
2. Use the cumulative probability that corresponds to the random deviate to extract values from the estimated CDFs at each grid cell

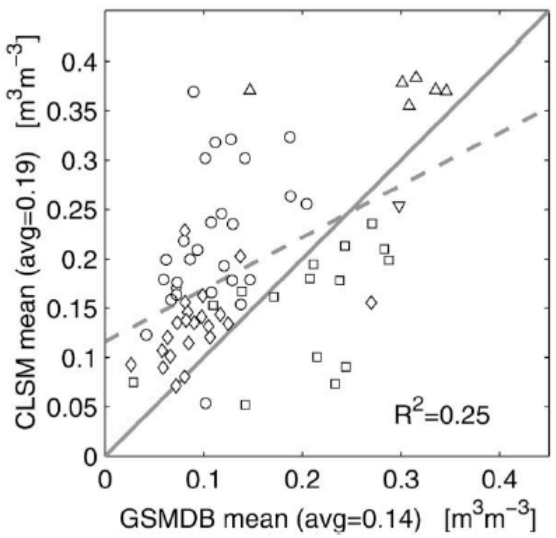




Rel?

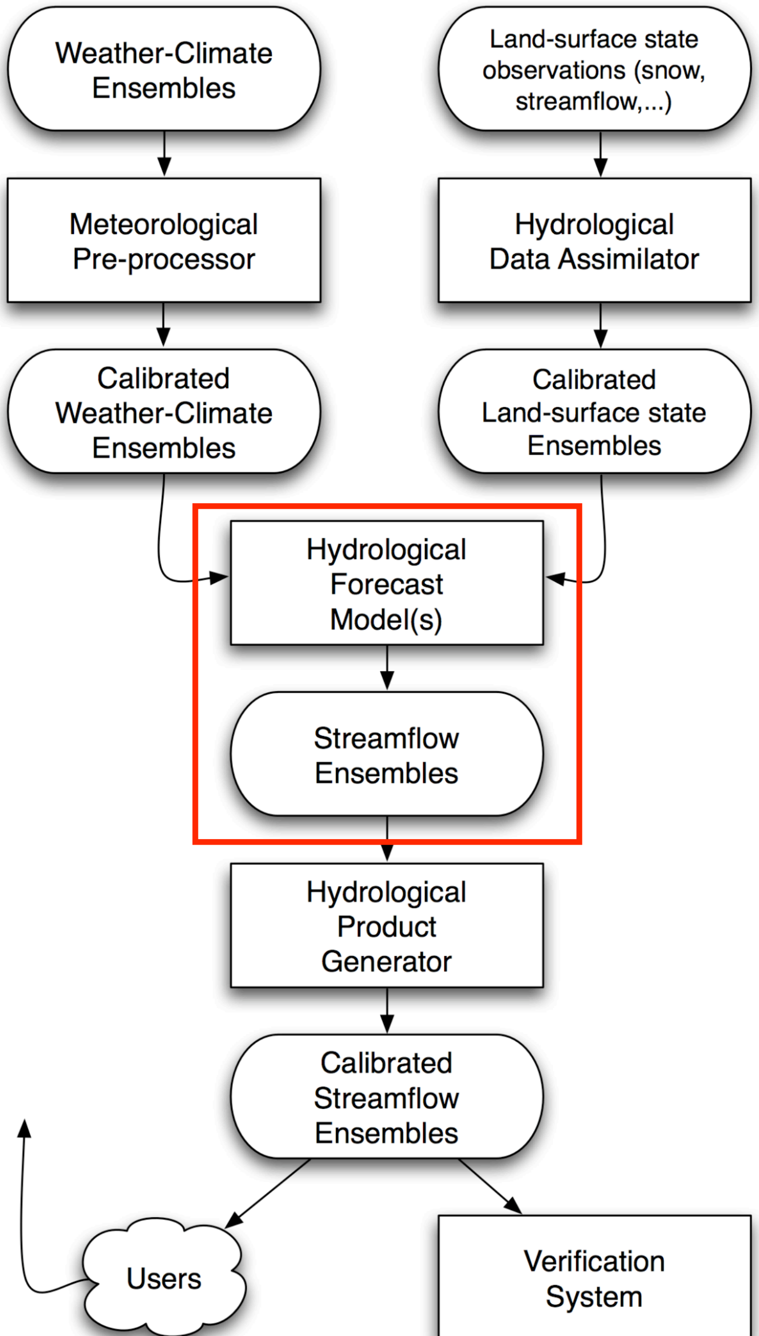
Land-surface model and satellite data in hydrologic data assimilation





- Use of land-surface model (LSM), satellite data desirable because in-situ measurements relatively rare.
- LSM: energy-balance model forced by observed temperature, precipitation; predicts snow, soil moisture
- Satellite: microwave data most commonly used; however, retrievals of soil moisture biased, complicated by estimates of surface emissivity.
- Here, CLSM (NASA catchment land-surface model) and SMMR (microwave satellite estimates) are compared against global soil moisture databank (GSMDB). Different symbols for different locations. Note large bias of both satellite, LSM relative to observations.

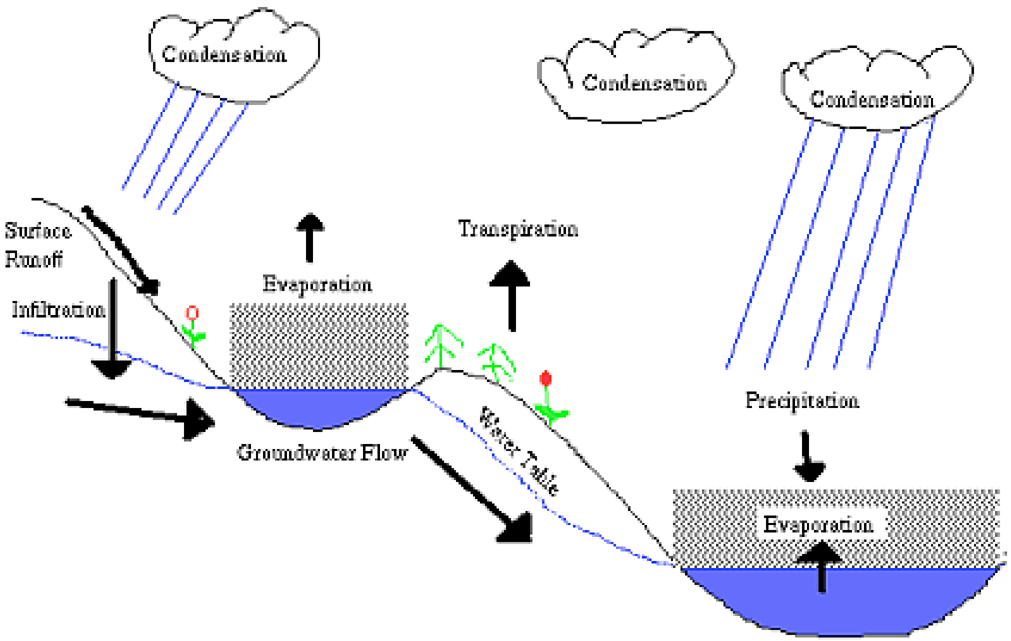
Ref: Reichle et al., *J. Hydrometeorology*, 2004.



Input the weather-climate ensembles and land / snow / streamflow ensembles into hydrologic forecast model(s), with multiple parameters or stochastic formulations to account for model uncertainty.

Note: in some systems,the hydrologic forecast model is simply some “routing” model. In others it may be a complicated land-surface model coupled with routing model. In the latter case, forecast information from the hydrological forecast model will be input back into the hydrologic data assimilator.

Hydrologic forecast basics

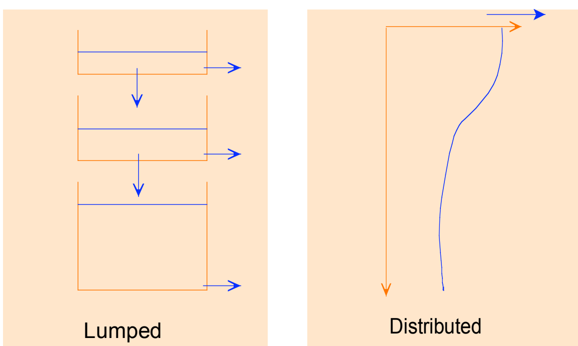


- **Infiltration** happens when the precipitation filters into the ground; some of which may be recovered by plant roots and be transpired. If enough infiltration then water may penetrate all the way down to the water table. The **water table** is the top layer of saturated ground that can be found across the planet. In places where the water table intercepts the land surface, it is manifested as wetlands, lakes and rivers. The water found below the water table is called **groundwater**. If there has not been any rainfall for several days the river flows are sustained by drainage from the groundwater reservoir (b**aseflow**); these flows will gradually decrease until the groundwater levels drop below the land surface.
- **Surface runoff** is when precipitation moves along the surface of the ground when either the ground can no longer absorb the water, or the ground cannot absorb the water fast enough. The water flows (via gravity) along the surface until it finds its way into a stream, river, lake, or ocean. Surface runoff causes the stream to rise quickly after heavy rains because it is the fastest way water can reach a river or stream, much faster than through infiltration.
- To be able to forecast the amount of water flowing through a certain point along a river, the forecaster breaks the flow down into three components: (1) **Baseflow**: the amount of water coming from groundwater. (2) **Runoff**: the amount of water coming from surface runoff. (3) **Routed Flow**: the amount of water coming from upstream areas.

Ref: http://www.srh.noaa.gov/abrfc/fcstmethods.shtml

Lumped vs distributed models

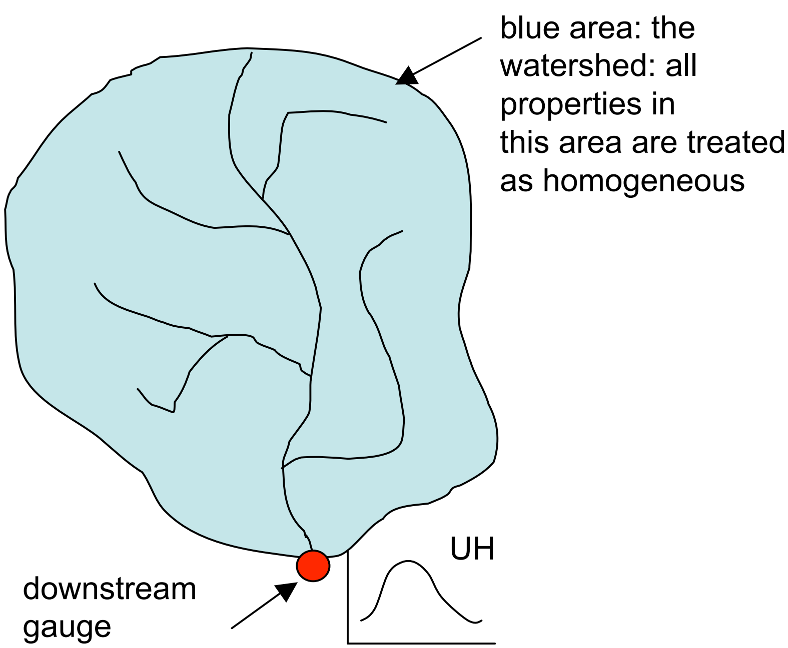
- **Lumped**: usually empirically based.
  - Watershed represented with uniform characteristics (Precip(avg), Slope(avg), Soils(avg), …)
  - Area runoff "signature" (unit hydrograph) and regression relationships commonly used
  - Predict flow distribution at watershed outlet
  - "When no spatial variability is taken into account and when the channel reach or reservoir is considered as a black box, the routing procedure is referred to as lumped routing."
  - Vertical transport: collection of slabs parameters controlling vertical water movement
- **Distributed:** usually "physically based"
  - Spatial variability within watershed accounted for (P(x,y), S(x,y), Soils(x,y), …)
  - Overland flow and channel routing represented with more spatial detail
  - Channel routing: translation of runoff hydrograph through channel reaches; route and combine at junctions
  - Diffusion equations for vertical water transport
  - "Propagation of flood waves in a river channel is a gradually varied unsteady process, which is governed by mass and momentum equations." Numerical solutions use the kinematic wave and (sometimes) dynamic wave equations

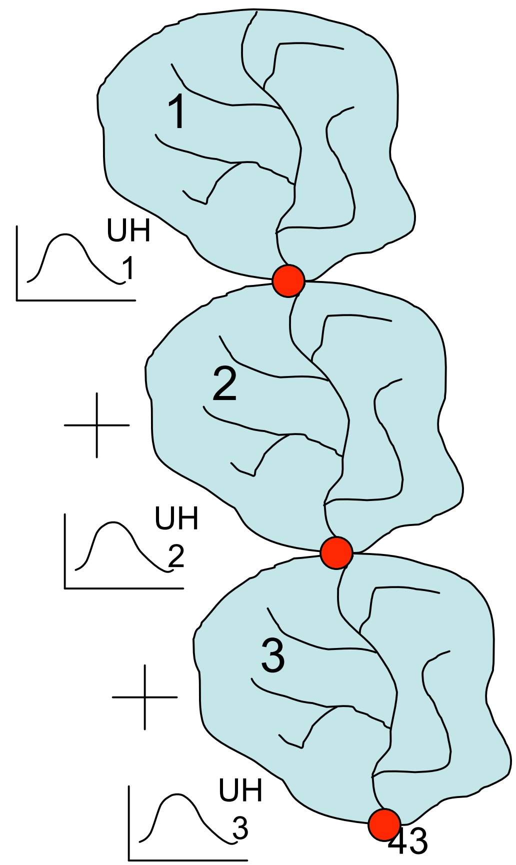


Refs: http://www.nws.noaa.gov/oh/hrl/distmodel/victor.ppt and
Ramirez, J. A., 2000: Prediction and Modeling of Flood Hydrology and Hydraulics Chapter 11, *Inland Flood Hazards: Human, Riparian, and Aquatic Communities*

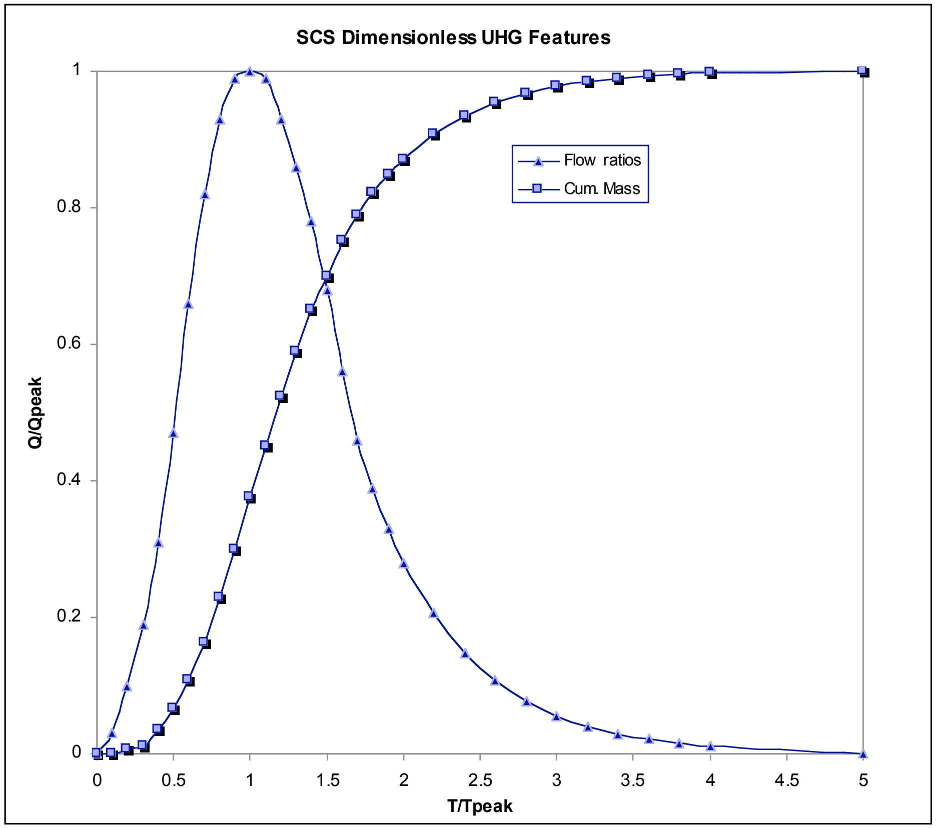
Lumped model

- Would like to predict flow at downstream gauge based on flow atmospheric drivers such as “precipitation excess”
- “Unit hydrograph” commonly adjusted to provide basin response to a unit pulse of excess precipitation (next slide)
- A river basin may be modeled as a collection of “lumped” sub-basins to obtain a semi-distributed model





"Unit hydrograph"



- A special hydrograph, called the **unit hydrograph**, is used to estimate how much water will be put into a stream by excess runoff. The unit hydrograph is based on the basin receiving enough rain in excess of infiltration to make one unit (cm, inch) of runoff, uniform over the basin for specified time period. The unit hydrograph shows how much of this inch of runoff will go into the stream in a specific amount of time.

- Linearity is assumed, so…

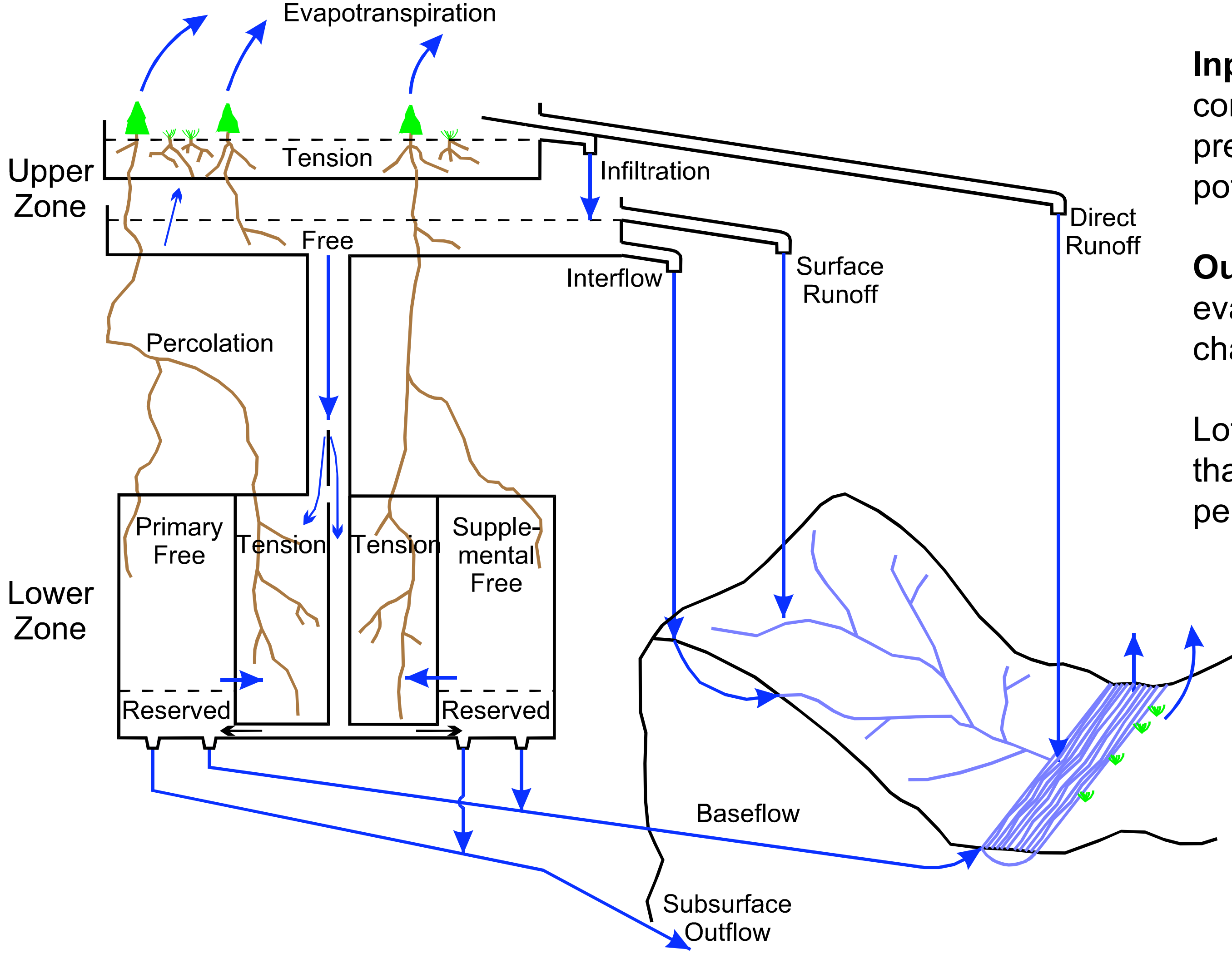
  (1) If, for instance, the runoff is something other than 1.0 cm, 0.1 cm for example, then multiply the unit hydrograph value by 0.1 to find the amount of flow into the stream.

  (2) Two separate pulses of rain can be modeled with the sum of two scaled unit hydrographs.

  (3) Time scale can be tuned lumped basin characteristics (size, slope, geometry).

http://www.weather.gov/iao/InternationalHydrologyCourseCD1/johnson/wmo_2003/lectures/6_uhg_theory.ppt

Sacramento Soil Moisture Accounting Model (a “lumped” model)



Inputs: initial hydrologic conditions, mean areal precipitation, temperature, potential evapotranspiration.

Outputs: estimated evapotranspiration, channel inflow.

Lots of model parameters that control aspects like the percolation rate.

Ref: National Weather Service River Forecast System Model Calibration briefing by F. Fiedler

Estimating lumped hydrologic model parameters and their uncertainty

Common approach: Force hydrologic model with "observed" meteorological conditions and upstream gauge data, tune model parameters until resulting flow at downstream gauge reasonably fits observed flow.

Problems / challenges:

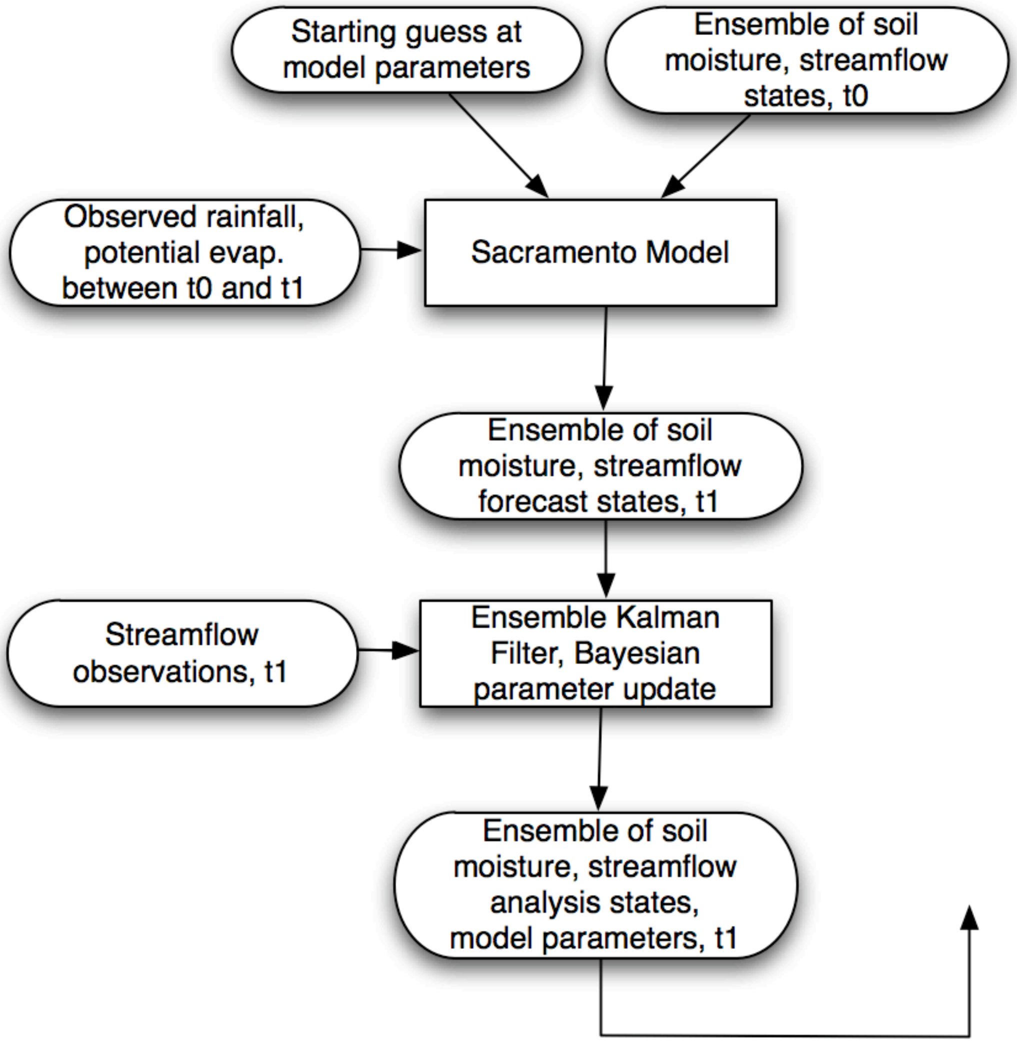
(1) Uncertainties in observed meteorological data accounted for?

(2) Why should parameters be considered fixed? Should they vary temporally, or spatially, or with the model state?

(3) Many parameters may need to be estimated. How does one simultaneously tune all of them?

(4) "Regulated basins" -- without natural streamflows, how do you calibrate?

Estimating hydrologic model parameter uncertainty

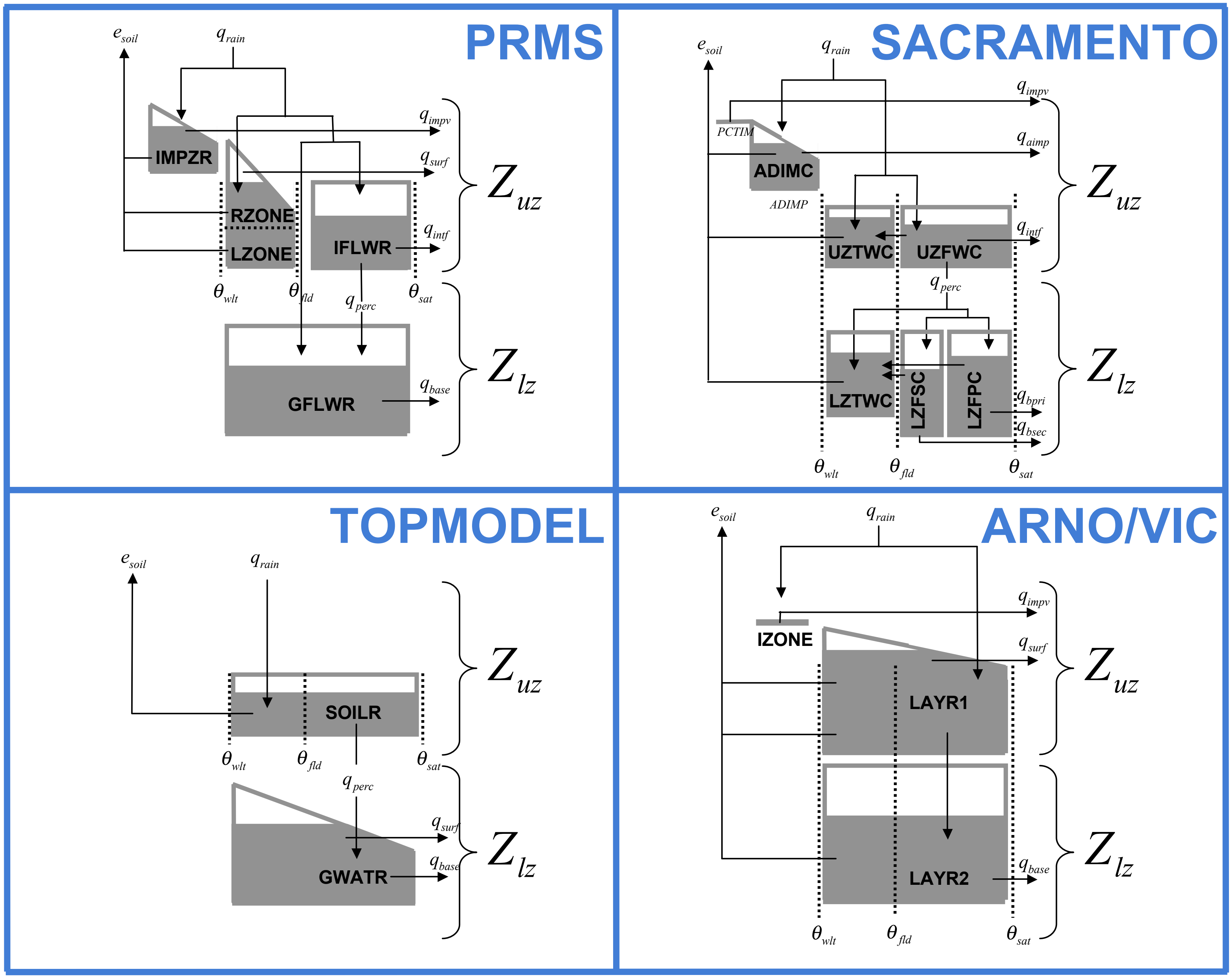


This process is repeated many times over in a Monte-Carlo process with different starting guesses at the model parameters and slightly different initial soil moistures and streamflow states.

After many years, the result is a distribution of parameter estimates.

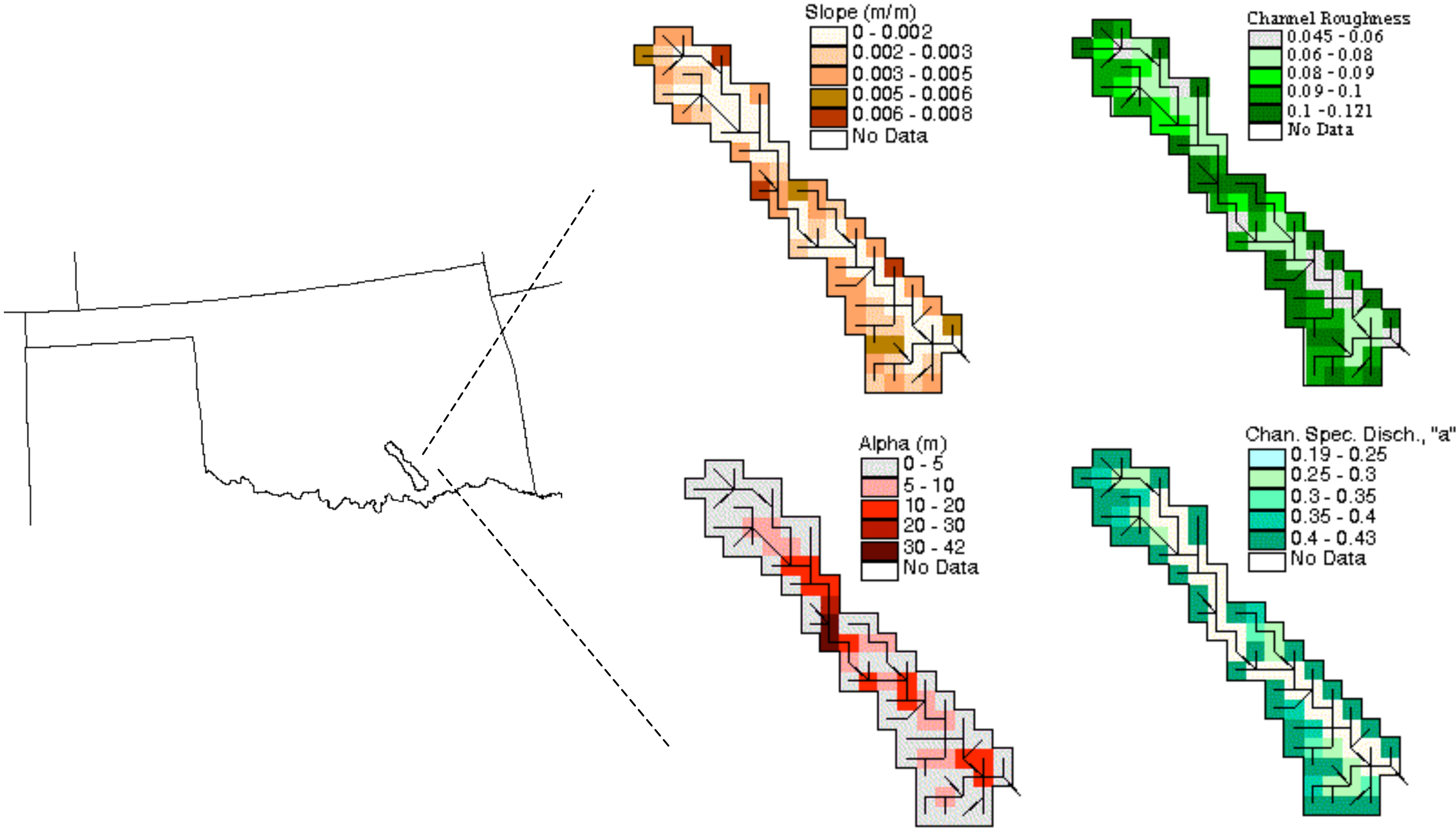
Ref: Vrugt et al., June 2006
J. Hydrometeorology

Estimate uncertainty using multiple models?



c/o Martyn Clark, NIWA

Distributed model example: basin in Oklahoma (central US)



Dynamical equations to model vertical water transport and flow downstream. Basin characteristics here estimated with data sources such as GIS data. Tuning may also be involved.

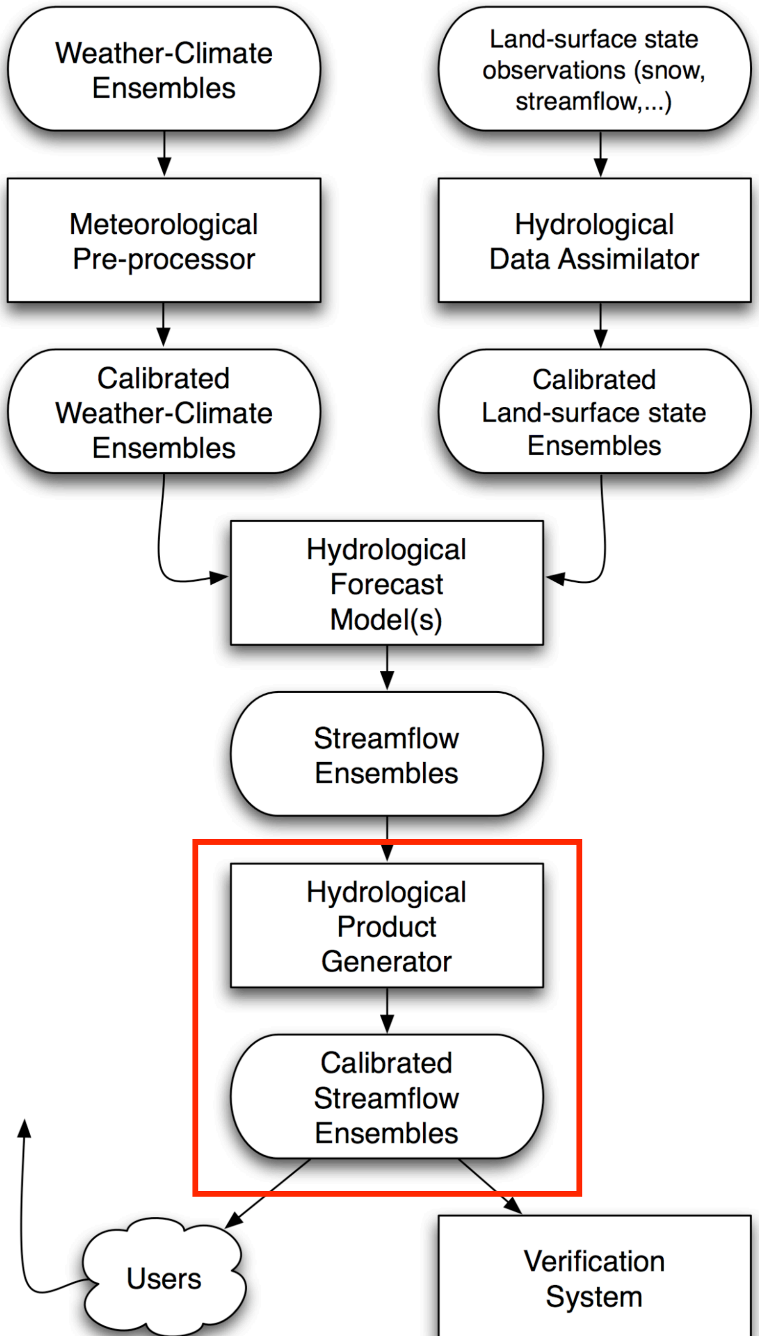
http://www.weather.gov/ohd/hrl/distmodel/distmod.htm

Issues with distributed models

(1) Despite conceptual appeal, distributed models are still not totally "physically based" -- still can require lots of ad-hoc assumptions, codified in profusion of parameters.

(2) Estimating parameters and their uncertainty for each sub-basin all that much more complex than for lumped model. There may not be enough observations …. parameter estimation subject to "statistical overfitting."

(3) For ensemble applications, require not only high-resolution databases, but also high-resolution quantification of uncertainty. Lots more work to do it "right"



Statistically adjust the streamflow forecasts, mitigating the remaining biases/spread issues, and tailoring the products to the formats most useful to the customers.

Statistically adjusting streamflows: "quantile mapping"

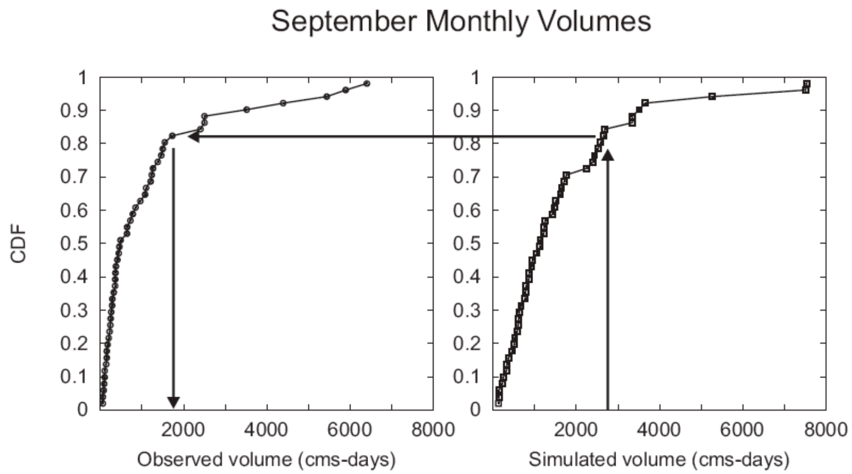
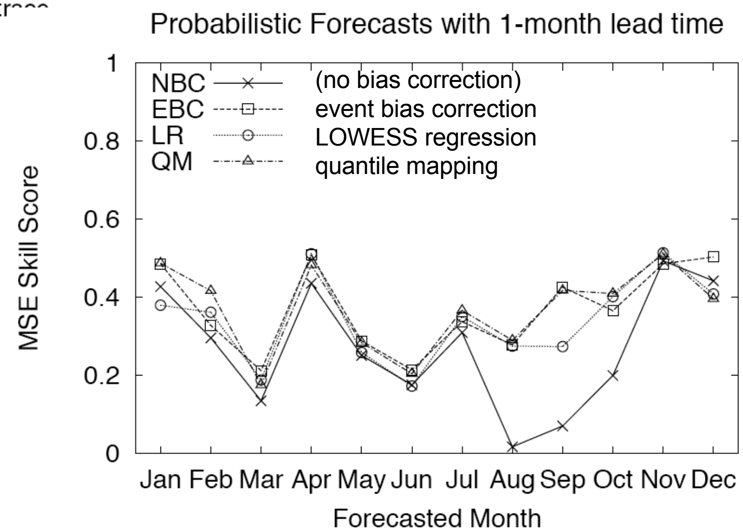


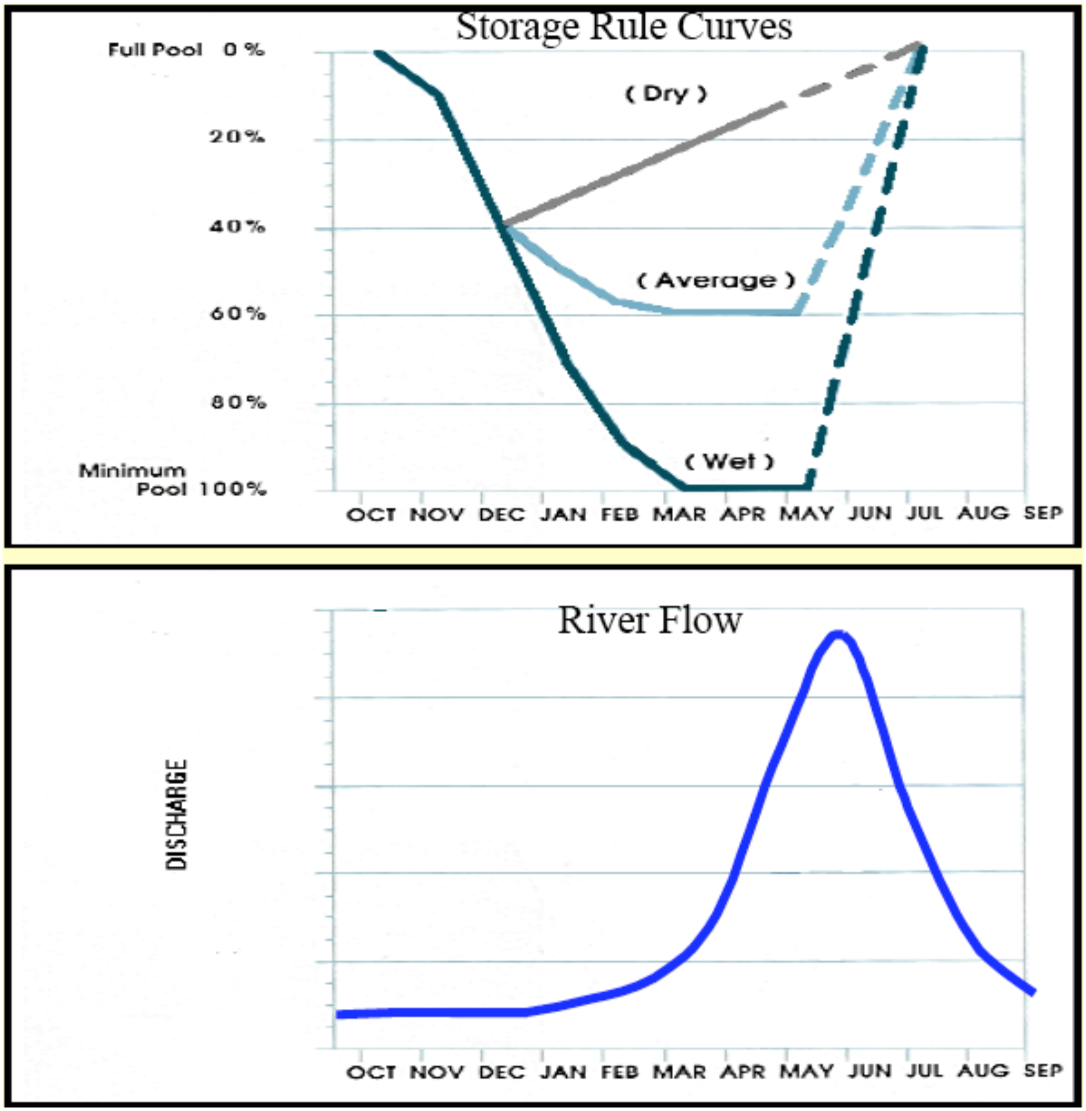
Fig. 4. Illustration of the quantile mapping method. The panels show the empirical cumulative distribution function for the observed and simulated monthly flow volume from the historical simulation. The arrows illustrate the transformation of an ensemble trace to the bias-corrected ensemble tr---



- ensures that CDF of corrected forecast consistent with CDF of observed.
- Many examples in hydrologic literature, here for basin in Iowa.

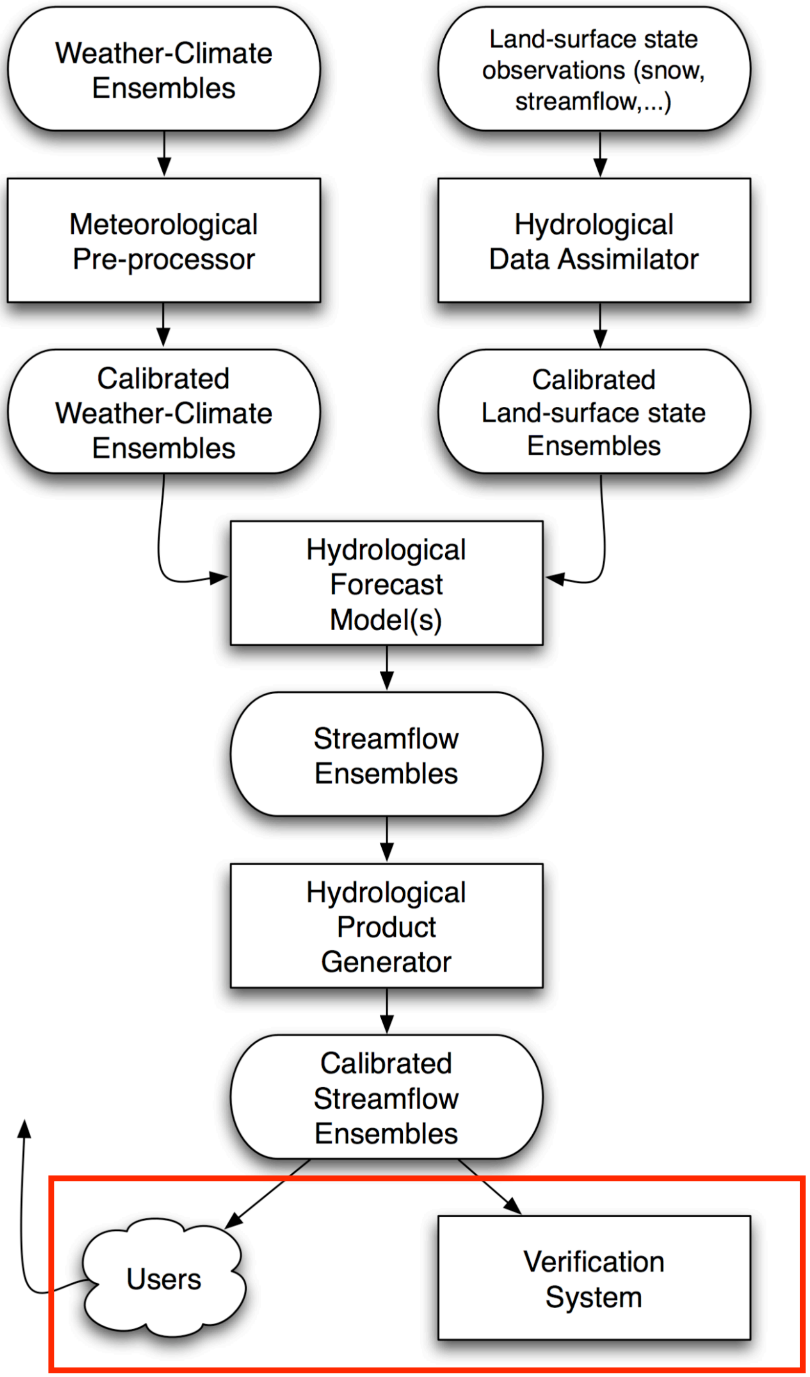
Ref: Hashino et al., 2006, Hydrology and Earth System Sciences Discussions

Understanding and tailoring hydrologic product for customers. Example: reservoir rule curves



- Large reservoir operators largely spill based on rule curves, with different rules to follow for dry, average, wet years.
- Represent compromises between storage for users (water supply, hydropower) and anticipated streamflow.
- Radically different streamflow forecasts from climatology may cause reservoir operator to follow a different rule curve.
- Possible product: translate ensemble streamflow forecasts into ensemble pool size forecasts.

Ref: “Flood control regional scale facilities” briefing, US Army Corps of Engineers

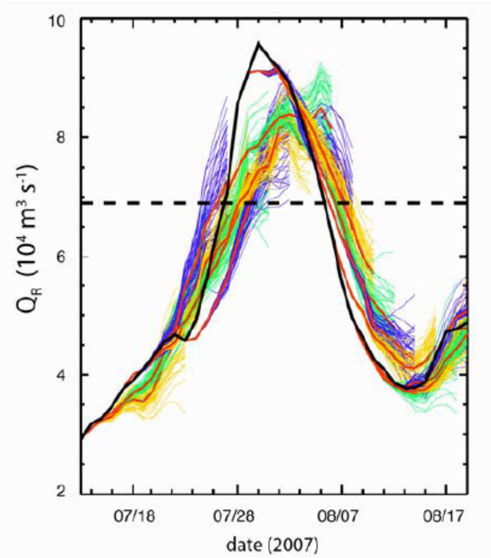


Monitor the forecasts, monitor the users' issues, and refine the process.

Validation / verification

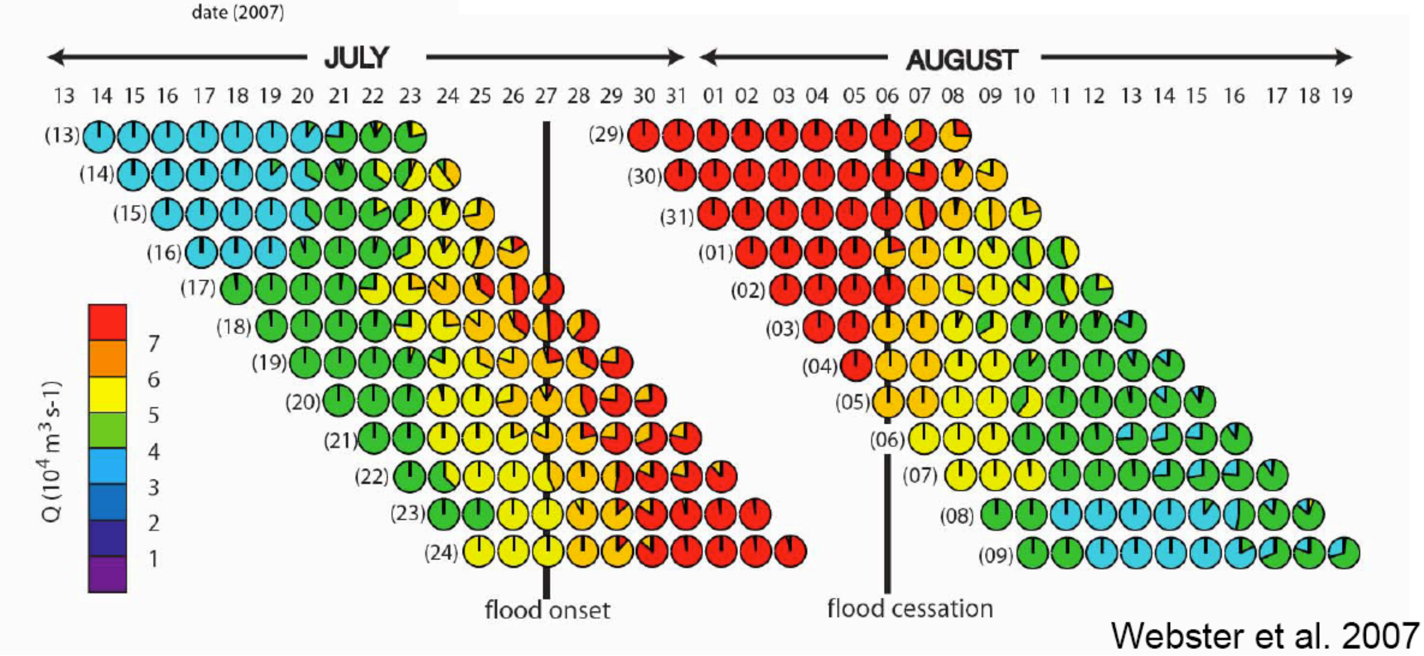
- Challenges:
  - (1) regulated basins. How to estimate unregulated flow?
  - (2) non-independent observations (today's & tomorrow's streamflows highly correlated, gauge here and a bit upstream highly correlated)
    - $\rightarrow$ long time series of forecasts to achieve large enough sample
    - $\rightarrow$ "reforecasts" very helpful.
- Many of the techniques used in atmospheric ensemble verification are still useful (reliability diagrams, skill scores, economic value, rank histograms, etc.)
- A few interesting new verification/display ideas

Display techniques



Plumes and probability pies for the first Brahmaputra flood July 28-August 6

- Short-term system was successful in providing high probabilities of exceedance of the danger level by the Brahmaputra at the India-Bangladesh border
- The forecasts were used for evacuation and etc



Webster et al. 2007

from ECMWF Nov 2007 workshop

Conclusions

- Weather-climate forecast inputs should be useful for probabilistic streamflow predictions.
- Must appropriately model errors from
  - Weather & climate forecasts
  - Estimates of land-surface initial conditions
  - Hydrologic models
- Need to better understand customers' decision problems and tailor products to be helpful in making useful decisions.

Short-range system in Italy

The coupled atmospheric-hydrological modelling system

The meteorological forecasting systems

- **COSMO-LEPS** is a Limited-area Ensemble Prediction System based on the non-hydrostatic limited-area model COSMO, daily running (12 UTC) at ECMWF since November 2002.

The different model runs are nested on some selected members of the ECMWF Ensemble Prediction System (EPS), chosen by means of an ensemble-size reduction technique based on a Cluster Analysis algorithm.

The system has been developed for the late-short to early-medium forecast range (48-120 h).

- The deterministic model COSMO operational at ARPA-SIM (**COSMO-LAMI**) is used as term of comparison to evaluate the added value of the probabilistic system.

The configurations (for the autumn seasons 2003-2005)

Name	Boundary conditions	Initial conditions	Moist convection	Prognostic precipitation	Horizontal resolution	Vertical resolution	Forecast range	Number of members
COSMO-LEPS	EPS forecasts	EPS analyses	Tiedtke or Kain-Fritsch (randomly selected)	yes	10 km	32 layers	132 h	10
COSMO-LAMI	DWD-GME forecasts	LAMI mesoscale assimilation (nudging)	implicit (Tiedtke)	no	7 km	35 layers	72 h	1

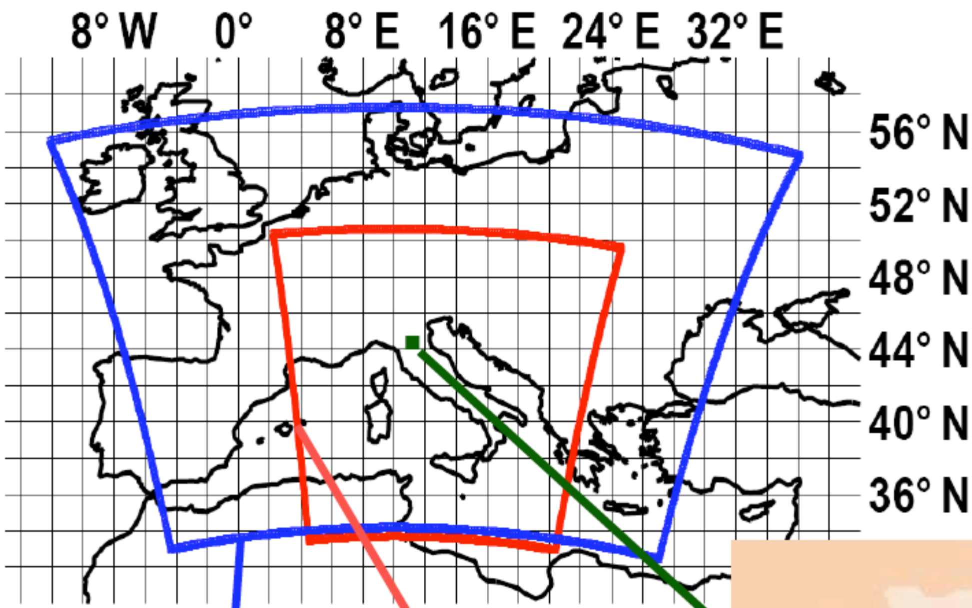
nb: for the COSMO-LEPS system of the year 2003 the forecast range is 120 h, the number of ensemble members is 5, the adopted moist convection scheme is Tiedtke and the prognostic treatment of rain and snow is not added.

The hydrological model

TOPKAPI (TOPographic Kinematic APproximation and Integration)
physically-based distributed rainfall-runoff model

[back]

Spatial Domains and Study Area



spatial domain of COSMO-LEPS

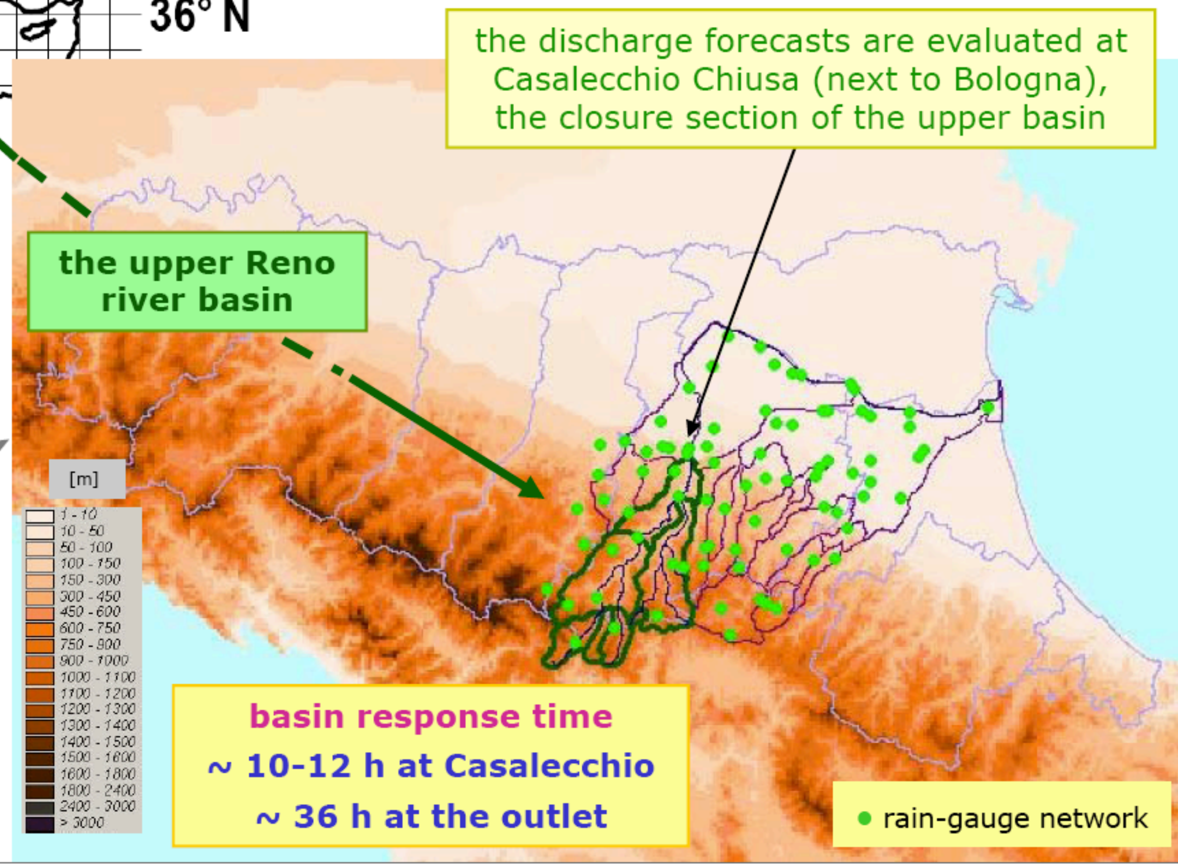
spatial domain of COSMO-LAMI

main river total length : 210 km

dimension : entire basin ~ 5000 km²
upper basin ~ 1000 km²

Alert threshold:
0.8 m (~ 80 m³/s) ***warning***
1.6 m (~ 630 m³/s) ***alarm***

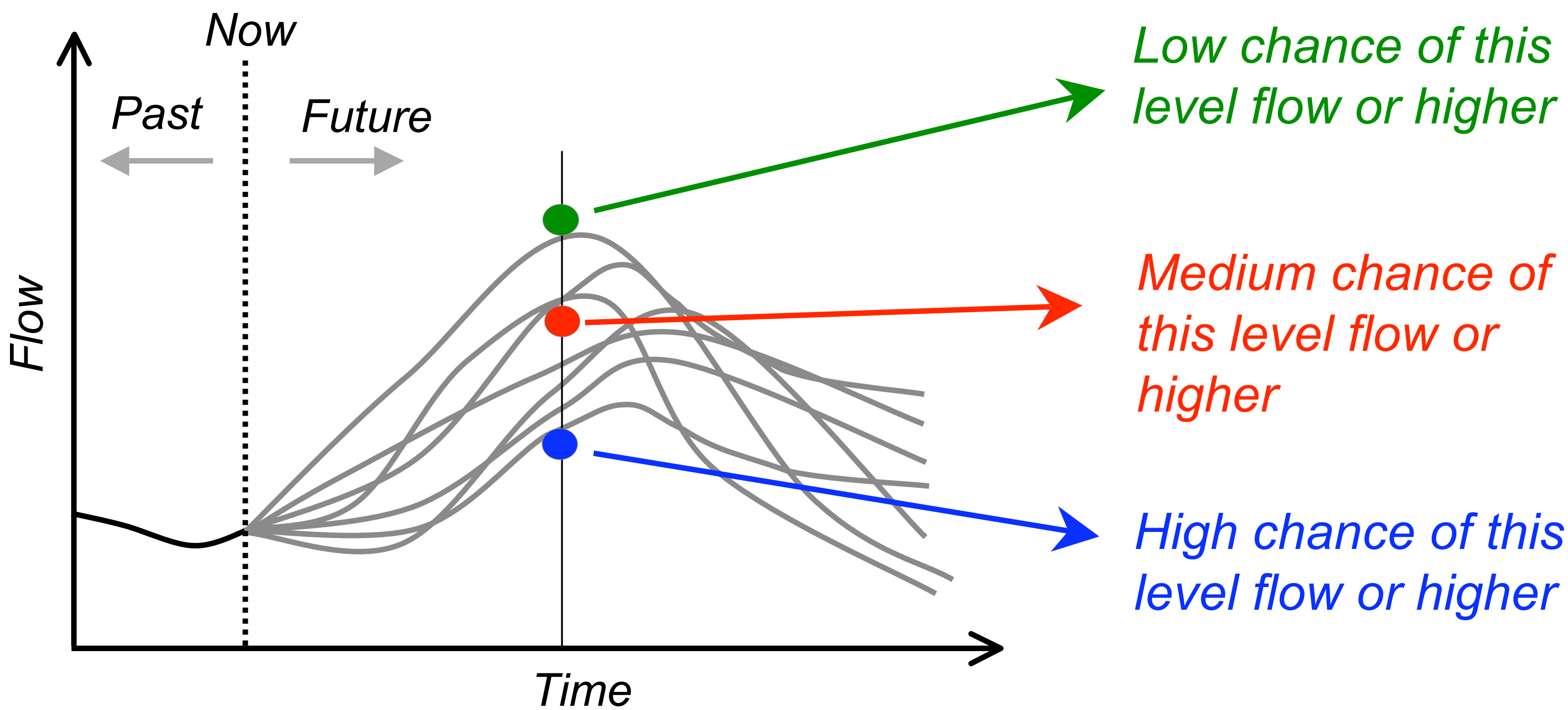
Emilia-Romagna Region



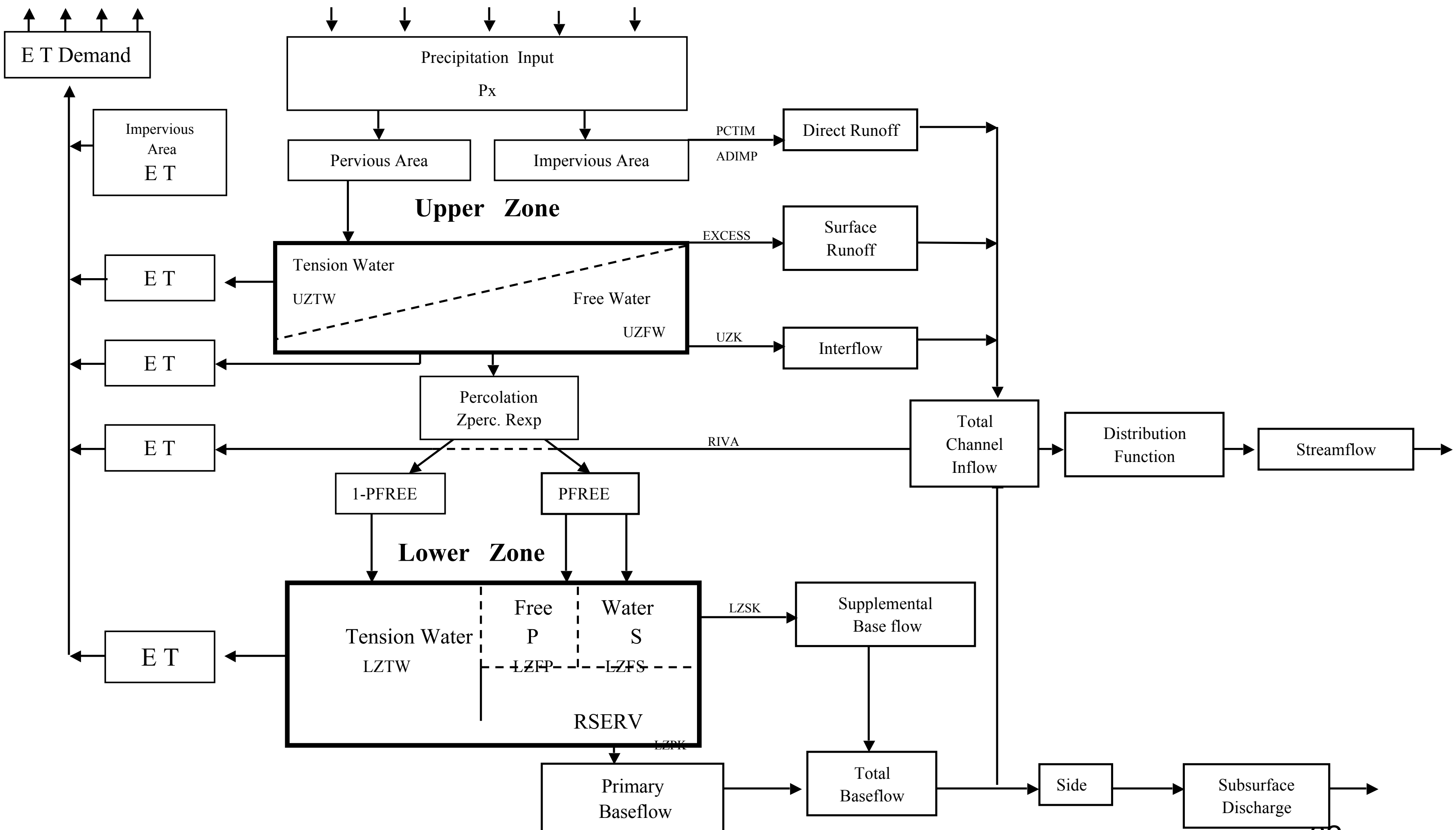
NOAA's reforecast data set

- **"Reforecast" definition:** a data set of retrospective numerical forecasts using the same model as is used to generate real-time forecasts.
- **Model**: T62L28 NCEP GFS, circa 1998
- **Initial States**: NCEP-NCAR Reanalysis II plus 7 +/- bred modes.
- **Duration**: 15 days runs every day at 00Z from 19781101 to now. (*http://www.cdc.noaa.gov/people/jeffrey.s.whitaker/refcst/week2*).
- **Data**: Selected fields (winds, hgt, temp on 5 press levels, precip, t2m, u10m, v10m, pwat, prmsl, rh700, heating). NCEP/NCAR reanalysis verifying fields included (Web form to download at *http://www.cdc.noaa.gov/reforecast*).
- Validation data for this study: North American Regional Reanalysis (NARR)analyzed precipitation (Mesinger et al., *BAMS*, 2006)
- **Real-time** downscaled probabilistic precipitation forecasts: http://www.cdc.noaa.gov/reforecast/narr

(3) ESP Technique (continued)

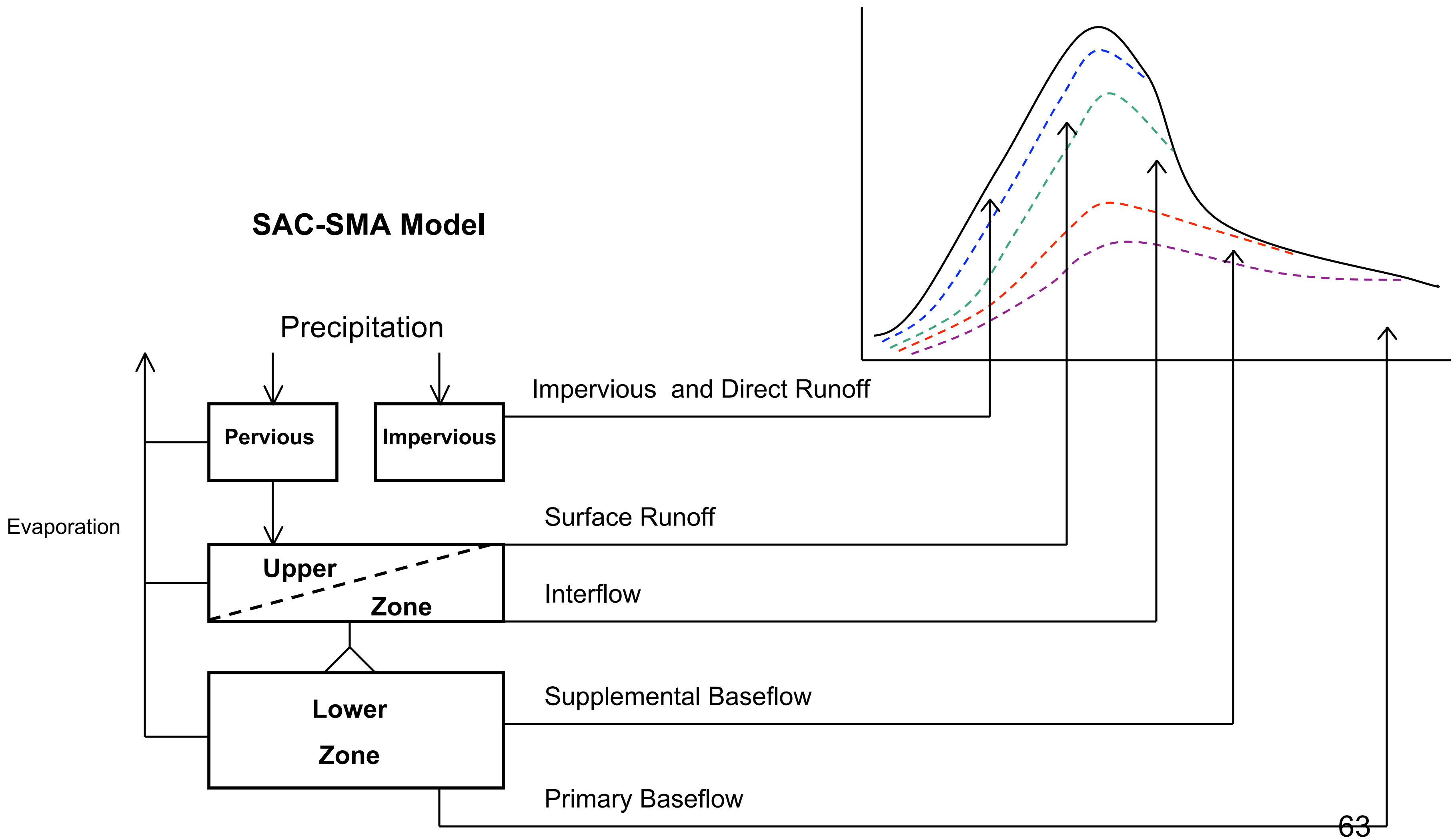


Sacramento Model Structure



Ref: National Weather Service River Forecast System Model Calibration briefing by F. Fiedler

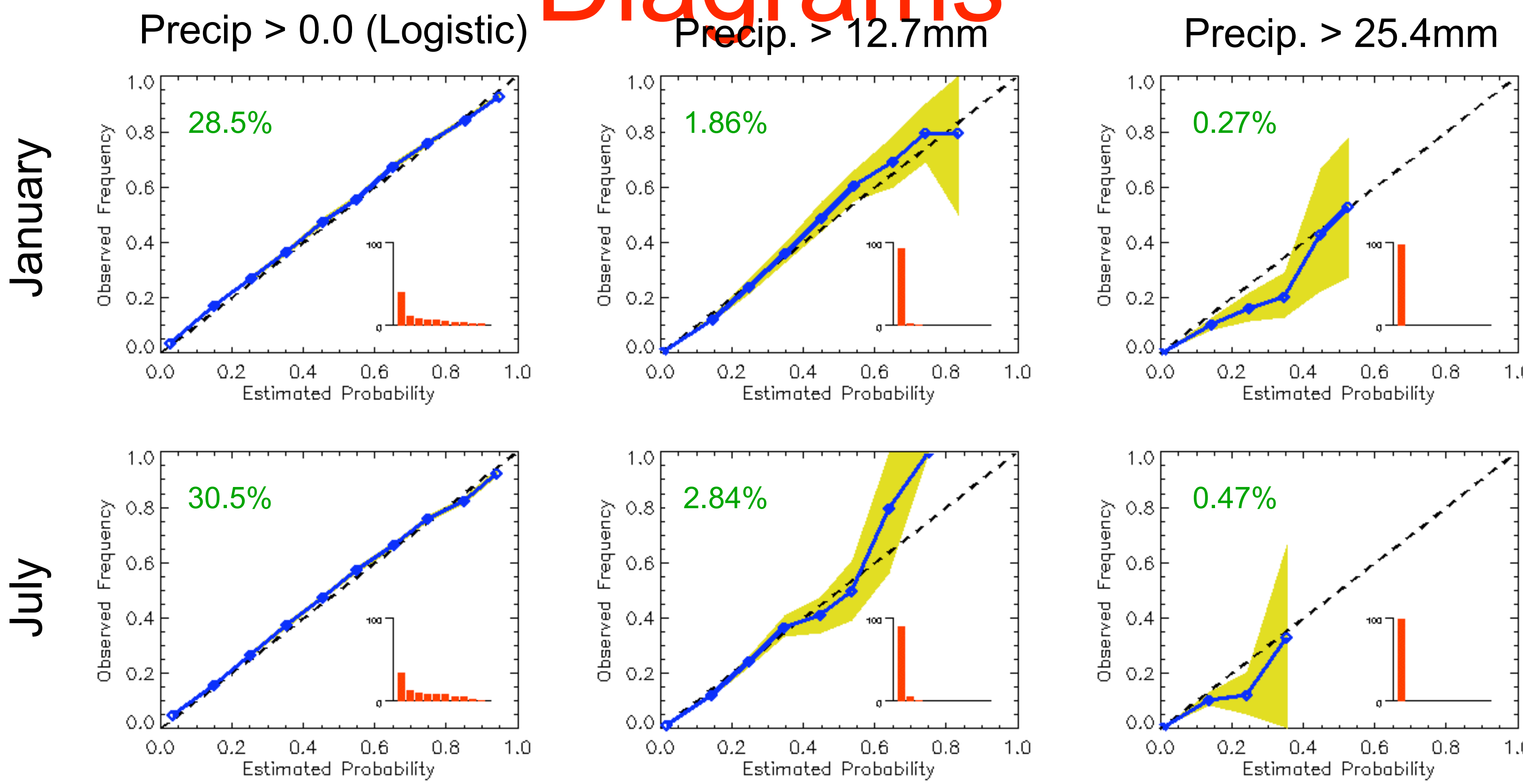
Sacramento model contributions to runoff



Ref: National Weather Service River Forecast System Model Calibration briefing by F. Fiedler

Verification : Reliability Diagrams

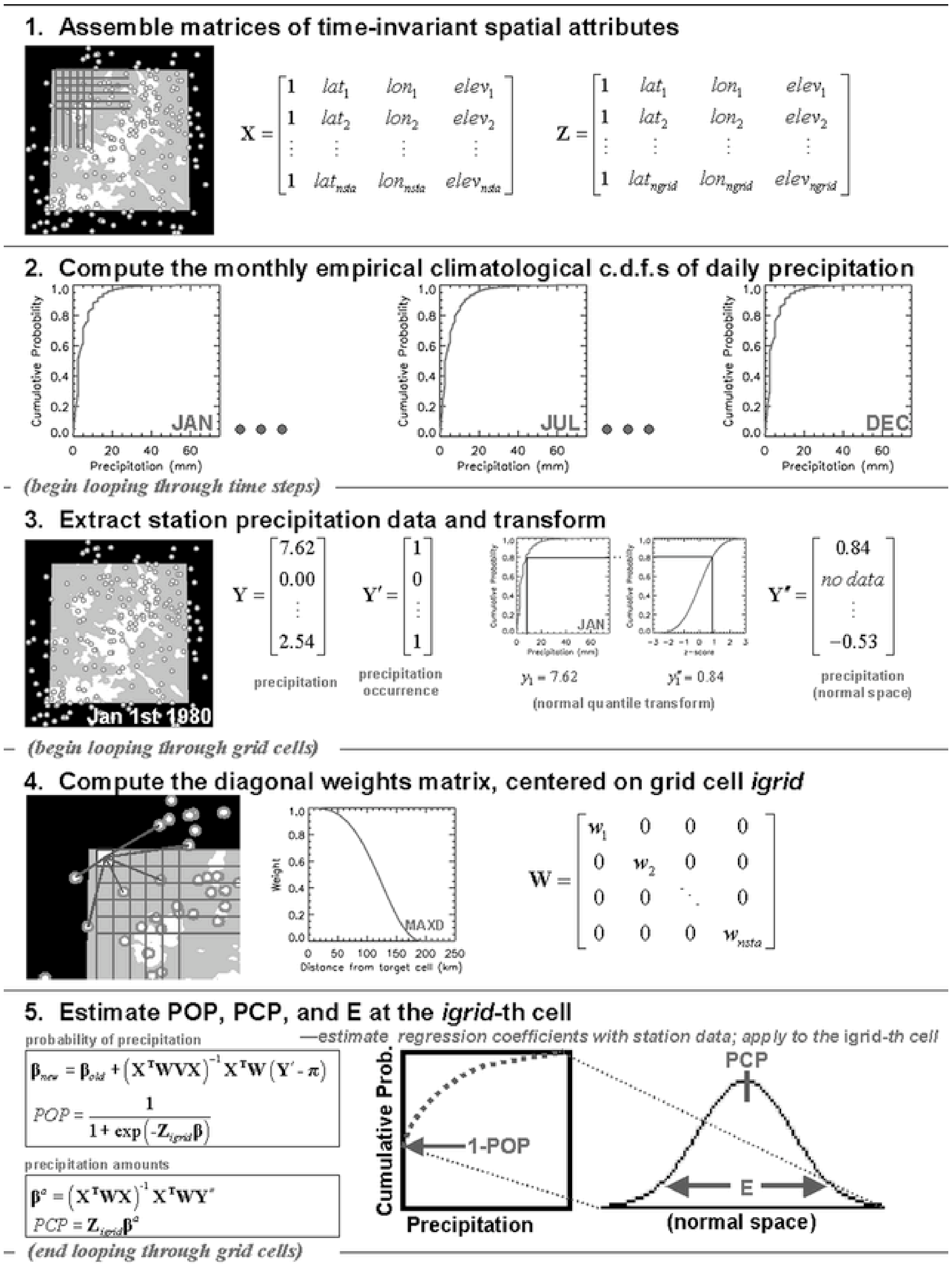
- Conditional probability that an event occurred, per category



% per category 95% confidence zone

[Back]

Clark and Slater (2006) – *Journal of Hydrometeorology*


1. Assemble matrices of time-invariant spatial attributes
X = [1 lat_1 lon_1 elev_1; 1 lat_2 lon_2 elev_2; ⋮ ⋮ ⋮ ⋮; 1 lat_nsta lon_nsta elev_nsta]
Z = [1 lat_1 lon_1 elev_1; 1 lat_2 lon_2 elev_2; ⋮ ⋮ ⋮ ⋮; 1 lat_ngrid lon_ngrid elev_ngrid]
2. Compute the monthly empirical climatological c.d.f.s of daily precipitation
Cumulative Probability
Precipitation (mm)
JAN
JUL
DEC
(begin looping through time steps)
3. Extract station precipitation data and transform
Jan 1st 1980
Y = [7.62; 0.00; ⋮; 2.54]
precipitation
Y′ = [1; 0; ⋮; 1]
precipitation occurrence
y1 = 7.62
y1* = 0.84
(normal quantile transform)
Y* = [0.84; no data; ⋮; −0.53]
precipitation (normal space)
(begin looping through grid cells)
4. Compute the diagonal weights matrix, centered on grid cell igrid
Weight
MAXD
Distance from target cell (km)
W = [w_1 0 0 0; 0 w_2 0 0; 0 0 ⋱ 0; 0 0 0 w_nsta]
5. Estimate POP, PCP, and E at the igrid-th cell
probability of precipitation
—estimate regression coefficients with station data; apply to the igrid-th cell
β_new = β_old + (XᵀWVX)⁻¹ XᵀW (Y′ − π)
POP = 1 / (1 + exp(−Z_igrid β))
precipitation amounts
β^a = (XᵀWX)⁻¹ XᵀWY*
PCP = Z_igrid β^a
Cumulative Prob.
1-POP
Precipitation
PCP
E
(normal space)
(end looping through grid cells)

[back]